PEER EFFECTS IN AGRICULTURAL EXTENSION: EVIDENCE OF ENDOGENOUS SOCIAL INTERACTION IN THE PERFORMANCE OF COMMUNITY KNOWLEDGE (EXTENSION) WORKERS IN UGANDA

BY

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THESIS

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Abstract

The *reflection* problem, as described by Manski (1993), is a major issue in the identification of peer effects due to endogeneity, which limits the possibility of separating the effects of the observed attributes of peers from that of social interaction. However, recent methodological advances in social network analysis (such as Cohen-Cole (2006); Moffitt (2001); Bramoullé, Djebbari, and Fortin (2009); De Giorgi, Pellizzari, and Redaelli (2010); Sacerdote (2001); Mas and Moretti (2009)) now show that it is possible to separate these effects. I utilize these rich theoretical methods and the empirical applications (e.g., Krishnan and Patnam (2014); Bramoullé, Djebbari, and Fortin (2009); De Giorgi, Pellizzari, and Redaelli (2010)) to empirically identify and estimate peer effects in the performance of rural extension workers, known as community knowledge workers (CKWs) in Uganda. I exploit a unique data set which comprise of administrative monthly records of the total monthly performance of CKWs (in terms of the agricultural information provided to farmers) as they deliver extension services to smallholder farmers in rural Uganda by means of smartphones which contain an agricultural information database. I separate the effects of peer outcomes on individual performance from those associated with group or social interaction. I use a pool of these total monthly performance records for a 13-month period including December 2010 to December 2011. The identification strategy utilizes the assumption of intransitive triads (Bramoullé, Djebbari, and Fortin, 2009) or partially overlapping peers (De Giorgi, Pellizzari, and Redaelli, 2010) within a network of interacting agents. I construct a panel data set that constitute the monthly performance of individual CKWs across 13 districts for

13 months of community extension operation by these CKWs. The approach identifies peer effects among CKWs in terms of their total monthly performance. This study contributes to the literature by being first to empirically estimate peer effects among extension workers based on their total monthly performance in the context of a developing country. The study has significant policy implications for improving agricultural extension in developing countries and elsewhere.

I dedicate this work to the glory of God almighty, whose I am and whom I serve. For in him I live, and move, and have my being (Acts 17:28, emphasis mine). All majesty I ascribe to him, through Jesus Christ my savior "through whom I have access by faith, into this grace in which I stand" (Romans 5:2, emphasis added).

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Chapter 1

Introduction

In this chapter, I present a detailed background information of the study and other relevant pieces of information such as the research question, the aim and motivation, the key hypothesis as well as the relevance of this study through its contribution to the extant literature.

1.1 Background information

Studies on peer effects, or the propensity of an individual's actions or outcomes to reflect the dominant outcome of his/her group or community (Manski, 1993), have received increasing attention in the social sciences, due to their salient implications across a wide variety of context (Bramoullé, Djebbari, and Fortin (2009); De Giorgi, Pellizzari, and Redaelli (2010); Manski (1993); Sacerdote (2001); Mas and Moretti (2009); Ioannides and Zabel (2008); Fortin and Yazbeck (2011)). For instance, workers with high productive ability improve the performance level of a team compared to their counterparts with lower abilities. This finding has vital implications for employers and human resource managers in terms of staff allocation to duty, pairing or teaming (Mas and Moretti (2009); Herries, Rees, and Zax (2003)). Similarly, peer effects among students provide information on their academic outcomes and social decisions such as fraternity membership (Sacerdote, 2001) and their choice of an academic major (De Giorgi, Pellizzari, and Redaelli, 2010).

Depending on the sub-discipline within the social sciences, peer effects are usually expressed by diverse related terminologies such as endogenous social effects, bandwagons, contagion, neighborhood effects, social norms, imitation, epidemics, peer influences, conformity, herd behavior, social interactions, and interdependent preferences. They all imply the propensity of an individual's outcome or behavior to reflect the dominant behavior within a group or community to which he/she belongs (Manski (1993); Bernheim (1994); Munshi (2003)).

Many studies demonstrate the significance of peer effects in explaining behavioral outcomes in diverse areas within the social sciences. For instance school achievement and academic performance (Sacerdote (2001); Markman, Hanushek, Kain, and Rivkin (2003); Zimmerman (2003); Cipollone and Rosolia (2007)), crime and delinquency causation (Glaeser, Scheinkman, and Sacerdote (1995); Patacchini and Zenou (2007); Bernasco, de Graaff, Rouwendal, and Steenbeek (2012); Loureiro, Mendona, Moreira, and Sachsida (2009); Calv-Armengol, Patacchini, and Zenou (2005)), participation in welfare programs (Bertrand, Luttmer, and Mullainathan (2000)), retirement planning (Duflo and Saez, 2003), the causes and prevention of obesity (Trogdon, Nonnemaker, and Pais (2008); Fortin and Yazbeck (2011)), and group cohesion and conformity (Bernheim (1994); Zimmerman (2003); Duflo and Saez (2003)). For example, decision making patterns among youths and young adults regarding certain behavioral outcomes like drugs abuse, sexual promiscuity and high school dropout rate from schools (Card and Giuliano (2013)). Some studies on peer effects have also centered on the probability of participating in labor markets within certain social class (Munshi (2003); Zenou (2012); Jackson (2005); and Topa (2001)).

Peer effects are assumed to have a large effect in contexts that rely on informal learning, such as agriculture in developing countries. Agriculture has been the focus of many studies on peer effects especially in terms of technology adoption among rural farmers. Various studies find that peer effects significantly influence agricultural technology adoption among rural farmers in sub-Sahara Africa (Krishnan and Patnam (2014); Liverpool-Tasie and Winter-

Nelson (2012); Maertens and Barrett (2013); Conley and Udry (2010)). The effects seem to be especially through learning from neighbors (Conley and Udry (2010); Liverpool-Tasie and Winter-Nelson (2012); Krishnan and Patnam (2014); Foster and Rosenzweig (1995)).

Although agriculture is the mainstay of the economies of many countries sub-Sahara Africa, growth in agricultural production has been largely slow (Krishnan and Patnam (2014); Gautam and Anderson (1999); Gollin, Parente, and Rogerson (2002)). The sluggish growth in agricultural productivity in the region compared to the rest of the world, has prompted the design and implementation of various intervention programs to improve agriculture in sub-Sahara Africa. For instance, Krishnan and Patnam (2014) state that;

> there has been enormous interest in replicating the Asian green revolution [in sub-Sahara Africa]. Thus, the focus has been on new technologies, particularly the adoption and diffusion of improved seed varieties and the increased use of fertilizer, supported by investments in effective extension services (p.1).

Agricultural extension is widely recognized as a crucial aspect of agricultural development (Knutson (1986); Eidman (1986); Eidman (1986); Lipton and Longhurst (1989); Dinar (1996); Norton, Alwang, and Masters (2006)). However, low performance of agricultural extension remains a major hindrance to agricultural development and consequently to economic development in many countries within sub-Sahara Africa. Thus, attempts have been made to improve extension as a means of improving agricultural production in the region.

However, a key challenge exists regarding the measurement of the precise impact of extension systems due to difficulty in impact attribution to extension. It is hard to quantify the output of extension and make direct recommendations on agricultural productivity (Feder, Lau, and Slade (1987); Knight, Johnson, and Finley (1987)). Therefore, there is gap in the literature on agricultural development due to a lack of quantitative analysis of extension as a major sector of agriculture. In particular, little study has been done on the labor outcomes of extension workers in developing countries especially in sub-Sahara Africa where the extension system remains widely unproductive (Gautam and Anderson, 1999).

Many studies that have attempted to quantify the performance of extension systems, have ran into hurdles leading to conclusions that were somewhat regarded as inconclusive. For instance, Gautam and Anderson (1999) reviewed a quantitative estimate of the performance of extension systems in Kenya and few other countries in sub-Sahara Africa as part of an assessment for the World Bank. They find significant flaws with previous analyses on the subject. Thus, they suggest stated;

> To firmly establish the achievement of concrete results [on the performance of extension systems] and to draw broad policy implications, the need to rigorously establish impact and to validate the empirical findings in other settings with the use of appropriate data, cannot be overstated (Gautam and Anderson (1999), p.12)

Thus, I empirically estimate peer effects in the performance of community knowledge workers (CKWs) in rural Uganda as a means of providing quantitative evidence for the performance of extension workers. I utilize a novel data set comprising of the administrative monthly records of CKW performance over a 13 - month period spanning December 2010 to December 2011. Performance is measured by the total monthly number of *searches* done by each CKW[1]. The CKW program provides a monthly record of the individual performance of all CKWs by district in Uganda. I limit the analysis to a 13-month period (from December 2010 to December 2011) across 13 districts for which data was available[2].

I analyze the total monthly performance of 650 individual CKWs across 13 districts in Uganda. These CKWs work at the parish[3] level within the districts of Uganda where

[1]CKWs work by providing agricultural information for farmers in response to specific needs of farmer. The information obtains from an agricultural database in the smartphones used for CKW operation. The process is referred to as a *search*

[2]The data for this analysis comes from administrative data on the monthly performance records of CKWs obtained from the country office of Grameen APLAB (Application Lab) in Kampala, Uganda

[3]A parish is the smallest administrative unit in Uganda. Depending on size, some parishes may be served by have more than 1 CKWs at a time

Grameen foundation operates the CKW program as a rural extension project. I focus the analysis at the district level because I assume that interactions among CKWs are partially overlapping across parishes and districts. I employ recent techniques in social networks analysis, using specifically, the empirical approach of Bramoullé, Djebbari, and Fortin (2009), and its application in Krishnan and Patnam (2014).

In my econometric strategy, I use the linear-in-means model which has been extensively utilized in analyzing social interactions (Cohen-Cole, 2006), to identify peer effects in the performance of CKWs as rural extension workers. I use the total monthly number of searches done by CKWs, as proxy for their total monthly performance. In the analysis, I consider each of the 13 selected districts as a spatial unit. These together form a spatial network where interactions are structured among CKWs. I assume that these interactions are not necessarily structured within groups in those districts, but rather, there is freedom of interaction in the entire network (i.e., the block of all districts). In other words, interactions among peers are overlapping in this setting. Thus, I argue that since the work of CKWs involves the use of cellphones with which they are also allowed to make private communication, the assumption of overlapping peers is plausible because it it possible for CKWs to interact across districts using their cellphones. Further, I assume that each district has a strictly exogenous and stochastic interaction matrix through which interactions are enhanced within a general network framework which comprise of all 13 districts in the study[4].

The left-hand side variable is the total monthly performance of CKWs. The right-hand side variables include dummies for own characteristics such as gender[5], whether a CKW owns a means of transportation such as bicycle, whether a CKW works in a hilly terrain,[6] whether a CKW is a household head, whether a CKW is married, as well as

[4]See for instance, the empirical application of Bramoullé, Djebbari, and Fortin (2009)

[5]Dummy for gender equals 1 if CKW is male, and 0 otherwise. I use a similar coding for the other dummies

[6]These two variables - i.e., hilly terrain and transportation affect transaction cost for a CKW

continuous variables including the total number of trainings sessions attended as a CKW[7], age, number of children, household size, the amount of money owed in debt, as well as the average characteristics of their peers (i.e., exogenous social effects variable) and their mean performance (i.e., endogenous social effects variable).

This study contributes to the literature in three ways: First, it pioneers an empirical estimate of the performance of extension workers through peer effects. Second, it provides evidence-based suggestions about the sustainability of extension systems through a component-by-component analysis of the performance of extension workers. Previous studies, including Knight, Johnson, and Finley (1987) only take a composite look at extension systems without regard to their internal workings and dynamics, especially in a robust quantitative manner. Such *black box* analyses fail to provide a clear picture of extension, and thus cannot make adequate predictions about sustainable performance of extension.

I hope to start the process of filling this gap in the literature. For instance, unlike Knight, Johnson, and Finley (1987), I analyze the performance of extension by using the outputs of extension workers through peer effects. This has vital implications for managing extension program delivery in developing countries. Third, this research provides a strategic answer to the important question on the industrial organization of extension. Peer effects provide vital information on the allocation of workers for optimal productivity (Mas and Moretti, 2009). This is critical in the face of dwindling funding to extension which has prompted a growing demand for guidance on how to better coordinate resource allocation for efficient delivery of extension services. Studies on worker productivity in other sectors (Umali-Deininger (1997); Mas and Moretti (2009); Maertens and Barrett (2013)) suggest that the identification of peer effects among a set of workers can guide their employers to make crucial management decisions such as organizing them into teams and setting individual wages and salaries. The study provides meaningful guidance towards the critical issue

[7] This variable is simply referred to as *number of trainings*

of optimality in extension worker performance through appropriate means of allocation of extension staff in the field. The findings from this analysis may inform the design and implementation of extension programs in developing countries and elsewhere.

1.2 Aim of the study

The aim of this study is to determine whether peer effects exist in the performance (i.e., labor outcomes) of community knowledge workers (CKWs) in rural Uganda. I measure performance by the total monthly number of *searches* done by individual extension workers as captured by their monthly target records obtained at Grameen APLAB over a 13 - month period including December 2010 to December 2011.

The strategic objective for using the performance of extension workers to study the performance of extension as a system is based on the problem of attribution associated with measuring the impact of extension workers on farm productivity. It has been acknowledged that due to the difficulty of precise attribution to extension services, difficulty arises in attempts to separate the actual impact of extension services on farm productivity from other confounding factors such as agronomic and climatic factors. Such difficulty is a bottleneck in conducting precise evaluation or estimates of extension programs (Feder, Lau, and Slade (1987); Davis (2008)).

I argue that using the total monthly performance of extension workers (represented by these CKWs) provide a good proxy for the performance of the extension system in Uganda. Such estimate can be generalizable to similar settings across the developing world, especially within sub-Sahara Africa.

1.3 Research question

The key research question to which this analysis seeks to provide answers pertains to whether there are peer effects in the performance of agricultural extension workers, as it is in other sectors such as education, retail industry, to name a few. In other words, what drives the correlation between the performance of individual extension workers (known as community knowledge workers) in the study area? i.e., do peer effects account for the correlation between the individual performance of community knowledge workers across rural Uganda?

1.4 Hypotheses

The null hypothesis (H_0):

Since I don't know ex-ante, whether there is any significant effect of peers on the individual monthly performance of community knowledge workers (i.e., CKWs) in the research setting, I hypothesize that there are no peer effects among these CKWs in particular, and thus, posit that there are no peer effects among extension workers in general, in terms of their performance.

Alternative hypothesis (H_1):

From the theories of social interaction and conformity (Bernheim (1994); Manski (1993); Akerlof (1997); Jackson (2005); (Bramoullé, Djebbari, and Fortin, 2009)), I conjecture that a-priori, individual CKWs interact with their peers in their daily activities of providing extension services to rural farmers in their local communities within and across respective districts, using cellphones as the main tool of interaction. I assume that such interactions are partially overlapping, and generate peer influences in the outputs of these CKWs as expressed by their monthly performance. Hence, I posit that there are peer effects in the performance of agricultural extension workers, especially CKWs in Uganda.

1.5 Motivation

This research is motivated by the observation that the total monthly performance of individual community knowledge workers (i.e., CKWs) working across rural Uganda tend to be correlated as shown by administrative records of their monthly performance. Thus, it is necessary to investigate whether peer effects abound among these extension workers. Identification of peer effects has a wide range of vital policy implications. For instance, identifying peer effects can inform the construction of efficient models to reflect behavior and help predict future outcomes under identical or closely identical conditions (De Giorgi, Pellizzari, and Redaelli (2010); Manski (1993);Mas and Moretti (2009); Bramoullé, Djebbari, and Fortin (2009); Trogdon, Nonnemaker, and Pais (2008); Bertrand, Luttmer, and Mullainathan (2000); Duflo and Saez (2003); Akerlof (1997)). For example, Sacerdote (2001) shows that through peer effects, it is possible to reliably determine whether an in-coming college student might join a fraternity/sorority, as well as predicting the type of such fraternity/sorority the student would chose to join, after deciding to join. Moreover, through performance data on supermarket cashiers, Mas and Moretti (2009) suggest that peer effects among retail workers can help their employers to make informed decisions regarding wage settings and assigning such workers to specific tasks in order to maximize their performance or productivity levels.

Although peer effects, through social learning, have been studied in agriculture, predominantly in the context of technology adoption by farmers in various social settings (Conley and Udry (2010); Bandiera and Rasul (2006); Krishnan and Patnam (2014); Maertens and Barrett (2013); Liverpool-Tasie and Winter-Nelson (2012); Foster and Rosenzweig (1995)), I am not aware of any study on peer effects in the performance of extension workers, especially in a rural setting. This is due to the notion that it is difficult to do a quantifiable measure of the impact of extension workers due to the problem of lack of direct attribution of the impact of extension services on agricultural production, from the many confounding factors (such as weather, agronomy, and extension service) which influence agricultural productivity (Feder, Lau, and Slade (1987); Davis (2008)). I hope to contribute to the literature by using advances in social network analysis to provide estimates of the performance of extension workers through peer effects.

Moreover, within the general frameworks of development, especially regarding agricultural development and economic growth in developing countries, it would be needful to study peer effects in agricultural extension for the following reasons: First, there is increasing demand (both at policy level and the scholarly community) for evidence-based measures of the impact of extension in order to justify sustained funding to the sector (See Gautam and Anderson (1999); Anderson and Feder (2004); Anderson and Feder (2004); Knight, Johnson, and Finley (1987); Garrett (2001)). The current analysis pioneers an attempt to fill this important gap. Further, there is a growing demand for guidance on how efficiency in the agricultural sector can be attained, especially with regards to extension in developing countries. This is critical to sustainable development in sub-Sahara Africa through efficiency in agriculture since agriculture constitutes the mainstay of economic activities in the region (Umali-Deininger (1997); Maertens and Barrett (2013)).

Mas and Moretti (2009) also suggest that identifying peer effects among workers provides a useful guide to making informed decisions for setting wages as well as assigning them into the right mix of groups or teams to achieve higher productivity. I argue that extension workers are no exception. And as observed by Maertens and Barrett (2013), this is vital in the quest for efficiency in resource allocation to extension. Thus, I hope to make an inference on how to better improve extension as a sub-sector, especially for smallholder agriculture in sub-Sahara Africa and other developing countries.

Previous studies including Knight, Johnson, and Finley (1987), Betz (2009), and Dinar (1996) treat extension like a black box wherein each of the focus was mainly towards a cost-benefit approach to extension programs, with little or no emphasis on a component-by-component outlook. However, such *black box* analysis provides little guidance on how extension productivity can be maximized. Its main limitation is that it is hard to identify the key drivers of performance in extension.

Moreover, previous analyses fail to provide a solution to the problem of unsustainable financing of extension programs. Lack of sustainability in funding for agricultural extension especially for developing countries, such as those in sub-Sahara Africa, presents a serious threat to economic development. Thus, the current analysis is first of to attempt at delving into extension systems and studying the performance of its sub-components such as labor as measured by the monthly performance of CKWs. I am not aware of any previous analysis that has been done on extension workers' performance using peer effects. This study initiates an attempt to break the black box by doing a component-by-component analysis of the performance of extension.

Chapter 2

Literature review

This section presents a detailed review of the extant literature, including the theoretical and empirical literature on agricultural extension in relation to agricultural development, social networks in general, and peer effects in particular. I also provide information on how the present analysis fits into the extant literature.

2.1 Background to agricultural extension

Agricultural extension, commonly referred to as "extension", has a long history dating back to the 1800s, and was largely associated with the land grant university system in the United States of America (USA) (Garrett, 2001). The main goal of extension is to increase the knowledge and capacity of farmers with respect to improvement in farming practices in order to achieve higher levels of farm productivity (Feder, Lau, and Slade, 1987). Extension entails a complex mix of activities which comprise of knowledge dissemination through direct information to farmers, among other things Dinar (1996). Thus, investment in extension and agricultural research is considered a public good (Dinar (1996); Umali-Deininger (1997); McCunn and Huffman (2000)).

In the early days of the US extension system, extension was mainly directed towards people living on farms across the country (i.e., USA) and they benefited from agricultural research information from the land grant colleges (Knutson (1986); Garrett (2001)). The goal of extension at that time was "to identify research problems, especially those surrounding technology and improvements in agricultural production, and then transfer the research findings and resulting technology to farmers" (Garrett (2001), pg. 1).

Due to the huge benefits of extension as demonstrated in the US agricultural system, extension became adopted in many countries including those in sub-Sahara Africa. Thus, extension has become an integral component of agricultural systems (Davis (2008); Anderson and Feder (2004); Dinar (1996); Qamar (2005); Umali-Deininger (1997)).

Extension has evolved through various models and approaches including: - (1), transfer of technology (TOT), which was mainly applied in post-independent sub-Sahara Africa; (2), training and visits (T&V) system, which was conceived in the late 1970s to early 1980 (Gautam and Anderson (1999)), in order to address the perceived weaknesses of the "TOT" approach; and (3), the participatory extension approach (PAE), which was developed in the late 1980s and was considered to be more farmer-centered (Belay and Abebaw (2004,); Feder, Lau, and Slade (1987); Davis (2008)). Presently, extension is widely viewed within the context of *pluralistic extension*. This depends largely on the classification of the providers of extension services (Umali-Deininger (1997); McCunn and Huffman (2000)). Extension providers can be classified within any of the following three broad categories: 1). The public sector (such as national governments, through Ministries or Departments of Agriculture); 2). the private for-profit sector (represented by competitive non-governmental organizations (NGOs)), and 3). the private non-profit sectors, also represented by NGOs and institutions that do not seek a profit maximizing priority (Umali-Deininger (1997); Norton, Alwang, and Masters (2006); Picciotto and Anderson (1997)).

Extension services introduced in many developing countries, especially in sub-Sahara Africa, were patterned after the administrative set-ups of former colonial nations (Axinn and Thorat (1972); Belay and Abebaw (2004,)). Like other agricultural support services, extension services were mainly geared towards producing and marketing export commodities. Thus, crop-oriented extension programs were the norm in most of sub-Sahara Africa

(Picciotto and Anderson (1997), p. 249). However, since most of the extension systems patterned in such ways were not adaptive to local conditions, failure became inevitable (Belay and Abebaw (2004,); Feder, Lau, and Slade (1987)).

Recently lower government budgetary allocations to agricultural extension programs in developing countries especially in sub-Sahara Africa, necessitates a growing demand at policy level for appropriate means of rethinking the models of extension delivery in order to achieve efficiency (Dinar, 1996). For instance, traditional extension agents (i.e., those of the ministries and departments of agriculture) in sub-Sahara Africa usually ignore smallholder farmers in the rural areas and focus their attention to rich farmers. This hinders economic development in the region since the bulk of the farming population is involved in small scale agriculture (Dinar (1996); Belay and Abebaw (2004,); McCole, Culbertson, Suvedi, and McNamara (2014)). It is against this backdrop that Grameen foundation started the CKW program with the goal of "reaching the last mile" i.e., to the smallholder farmers[1].

2.2 Agricultural extension in the context of agricultural and economic development

The role of agriculture in economic development has long been at the fore (see for e.g., Lewis (1954); Fei and Ranis (1961); Evenson (1988); Birkhaeuser, Evenson, and Feder (1991)). In their classical piece titled 'A Theory of Economic Development', Fei and Ranis (1961) propounded the balanced growth model of development that lucidly articulates for the simultaneous growth of the agricultural sector and the industrial sector as a precursor for economic development (Christiaensen, Demery, and Kuhl (2011)).

Several factors have been advanced as viable for ensuring that agriculture develops

[1]See details at www.grameenfoundation.applab.org.

alongside the industrial sector in developing countries. The literature suggest that economic transformation in sub-Sahara Africa depends on a meaningful level of investment in some vital components of agriculture including agricultural research, education, and extension. For instance, Schütt (2003) argue that advancement in human capital causes a country to improve its capacity to adopt new or improved technologies, thereby leading to the possibility of *technological catch-up*. This helps to explain why sub-Sahara Africa still lags behind other continents in terms of agricultural outputs (Diao, Hazell, Resnick, and Thurlow (2007); Knutson (1986); Krishnan and Patnam (2014); Gollin, Parente, and Rogerson (2002)).

The extension system is widely perceived as a major driver of agricultural development (Birkhaeuser, Evenson, and Feder (1991); Dinar (1996); Lipton and Longhurst (1989); Haggblade (2007); Thorbecke (1970); Gollin, Parente, and Rogerson (2002); Picciotto and Anderson (1997); Garrett (2001); Fei and Ranis (1961); Nicholls (1970); Anderson and Feder (2004); Diao, Hazell, Resnick, and Thurlow (2007); Axinn and Thorat (1972)). Moreover, despite the attendant problems of attribution and lack of direct estimation of the impact of extension services on farm productivity and agricultural development (Feder, Lau, and Slade (1987); Davis (2008); Roe, Haab, and Sohngen (2004)), there is wide consensus about the relevance of extension in inducing agricultural transformation in sub-Sahara Africa (Birkhaeuser, Evenson, and Feder (1991); Anderson and Feder (2003); Haggblade (2007)). For instance, extension services help farmers with improved agricultural information (and training) thereby increasing their level of productivity (Anderson and Feder (2003); Dethier and Effenberger (2012); Umali-Deininger (1997); Dinar (1996); Belay and Abebaw (2004,); Anderson and Feder (2004); Knutson (1986)). Therefore, inefficiency in extension could translate to large problems in other sub-sector of agriculture in sub-Sahara Africa.

Large disparities exist in the level of efficiency and effectiveness of the components of agriculture especially extension in the region compared to elsewhere (Picciotto and Anderson (1997); Norton, Alwang, and Masters (2006); McCole, Culbertson, Suvedi, and McNamara

(2014)). Research suggests that aside extension, even the most improved technology might do little help to farmers, especially those in sub-Sahara Africa due to high levels of illiteracy and poverty among the farming population. Feder and Slade (1985) justify the vital role of extension in agricultural development thusly;

> the generation of new technology is a necessary, but not sufficient condition for increased farm productivity with given natural resources. In the short run, it is not even a necessary condition if there is a gap between available knowledge and typical farmer practices (p. 423).

This implies that a first principle for a meaningful investment towards sustainable agriculture should be accompanied by proportionate investment in extension which is crucial for improving the labor outputs in agriculture (Haggblade (2007); Knight, Johnson, and Finley (1987); Knutson (1986).

The relationship between the performance of extension workers and that of farm productivity among smallholder farmers in developing countries seems to have a positive correlation. Thus, a positive performance of extension workers can influence improvement the labor outcomes of the farmers they serve. On the other hand, weak performance of extension workers limits per capital productivity of farmers, especially smallholders (Belay and Abebaw (2004,); Knutson (1986); Anderson and Feder (2004); Aker (2011), Roe, Haab, and Sohngen (2004)). For instance, farmers consider the lack of information as a major deterrent to their participation in markets, and thus, as a disincentive for them to take greater risk and maximize their productive potentials by producing on a higher production possibility frontier (PPF) (Van Campenhout, Pauw, and Minot (2013); Nicolson and Snyder (2008.); Norton, Alwang, and Masters (2006); Stoneman and Diederen (1994); Feder and Umali (1993)).

On the flip side, high performance of extension workers will serve as an impetus to agricultural development by inducing high productivity of farmers (Christiaensen, Demery, and Kuhl (2011)). For instance, a positive correlation between the value of extension and agricultural development has been observed in the traditional extension systems through the direct visits of extension agents to farmers across various developing countries such as Kenya, Ethiopia, and Ivory Coast, to name a few (Bindlish and Evenson (1997); Gautam and Anderson (1999); Krishnan and Patnam (2014); Feder, Lau, and Slade (1987); Dinar (1996); Stoneman and Diederen (1994)). The situation has been particularly suspect for agriculture in sub-Sahara Africa. For instance, Gollin, Parente, and Rogerson (2002) observe that inadequate attention to extension remains a huge challenge in sub-Sahara Africa where agricultural development is slowest compared to the rest of the world (Gollin, Parente, and Rogerson, 2002).

In a comparative study of international productivity patterns across regions, Craig, Pardey, and Roseboom (1997) find that;

> Although sub-Sahara Africa experienced some moderate increase in land productivity over the past thirty years, labor productivity has been stagnant and there has been a dramatic decrease in the land-labor ratio.

Craig, Pardey, and Roseboom (1997) somewhat justify this lack of progress for sub-Sahara Africa compared to other regions of the world as follows;

> The regions with the highest research [and extension] spending per worker, highest literacy rates, and longest life expectancy are Europe, Australasia, and North America. These regions also have the highest measured land productivity. And those regions with the highest levels of output per worker-Japan and Western Europe-are those with the greatest road density in our sample (p.1068).

2.3 Agricultural extension and information communication technology (ICT): The link

A rich body of literature has emerged on the use of integrated approaches to agricultural development. This includes acknowledgment and use of information communication technologies (ICT) by farmers (Futch and McIntosh (2009); Gruber and Koutroumpis (2011); Hess (2013); Kostov and Lingard (2005); Godfray, Beddington, Crute, Haddad, Lawrence, Muir, Pretty, Robinson, Thomas, and Toulmin (2010)). The use of cellphones and other forms of ICTs are increasingly becoming a major part of the agricultural and rural economic systems in diverse areas of the developing world (see Chew, Ilavarasan, and Levy (2013); Ilavarasan and Levy (2012); Mittal, Gandhi, and Tripathi (2010); and Donner (2008)). This has positive effects on agricultural productivity in diverse ways including positive marginal cost-reduction benefits effects (Camacho and Conover (2011); Zanello (2012); Donner (2009); Donner (2008); Gruber and Koutroumpis (2011)). Research shows that sub-Sahara Africa is no exception to the increasing use of ICT, especially cellphones for various agriculture production activities (Zanello (2012); Porter (2012); Aker and Mbiti (2010)). For instance, Rwanda (Futch and McIntosh (2009)), Uganda (Svensson and Yanagizawa (2009); Muto (2012); McCole, Culbertson, Suvedi, and McNamara (2014)), and Niger (Aker (2010)) to mention a few.

Globally, ICTs, through cellphones, are increasingly becoming a social network tool particularly across developing countries. It is usually a means of acquiring information for employment as well as market for rural communities, especially farmers. For example, Jensen (2007) surmises the vital role of ICTs in agriculture and economic development thusly;

> The functioning of markets is a key determinant of the prices and availability of food, fuel, and other important consumer goods. However, in most developing countries, markets are dispersed, and communications infrastructure is poor.

> Producers and traders often have only limited information, perhaps knowing only the price in a handful of nearby villages or the nearest town, so the potential for inefficiency in the allocation of goods across markets is great. By improving access to information, ICTs may help poorly functioning markets work better and thereby increase incomes and at the same time, lower consumer prices (p.881).

Recently, sub-Sahara Africa has had a large penetration of ICT, especially through cellphones in the last decade. For instance, it is estimated that by 2008, the proportion of people subscribing to cellphones across many countries in the region had reached 37%, from 27% in 2006 (Muto, 2012). And many governments are making various reforms to expand cellphone coverage to the greater majority. For example, in Uganda, a regulatory reform in the telecommunications sector caused an expansion in cellphone coverage from 46.0%in 2003 to 80.0% of the population in 2006 (Muto, 2012). Moreover, it is reported that about 62% of people seeking jobs, a use personal networks to search for the search, by inquiring through cellphones (Muto and Yamano (2009); Muto (2012)).

Due to poor road and traditional communication infrastructure (such as telephone lines) in many countries in sub-Sahara Africa, the delivery of agricultural extension and information services to farmers in remote areas remain a serious impediment to agricultural development in the region. Thus, the introduction of ICTs especially the cellphone, is widely considered to have a high potential for agricultural development. For instance, ICTs provide support to rural communities that predominantly comprise of smallholder farmers in sub-Sahara Africa through various means such as money transfers and market information (Van Campenhout (2013)). Thus, access to agricultural information and improved technology through extension services to rural farmers reduces transactions costs and ensures higher profitability by reducing the propensity for asymmetric information and its concomitant vices (Svensson and Yanagizawa (2009); Nicholls (1970); Nayyar (1993); Nicolson and Snyder (2008.)).

2.4 Labor productivity in the context of agricultural extension

Labor productivity is fundamental in economic development in general, and agricultural growth in particular. The literature on labor productivity has evolved over the years, from the classical work of Fei and Ranis (1961) in the their seminal publication "A theory of economic development" which advanced the "balanced growth model" as a sequel to the "two-Sector Economy model" of Lewis (1954). Initially, Lewis (1954) proposed the notion that economic development (especially in developing countries) should be brought about by the transfer of agricultural labor (considered to be surplus and marginal with near zero productivity) to the industrial sector, where allocative efficiency is exists. However, Fei and Ranis (1961)argued that the agricultural sector must, as a matter of necessity, grow in tandem with the industrial sector during the course of a country's development. Otherwise, the contrivance in the two sector phenomenon could cause an economy to grind to a halt.

The idea of Fei and Ranis (1961) follows Rostow (1956) who argues that economic development usually begins with an initial departure from quasi-stagnation, which is the so-called take-off stage. And that a pursuit of this notion requires a balanced growth between agriculture and industry (Rostow (1956)). By implication, Fei and Ranis (1961) is consistent with the Malthusian theory of population in their proposition that sustainable development must follow the trajectory of a balanced-growth, thus putting a demand on developing countries to address capacity issues as a prerequisite for economic development. Labor productivity of extension workers could not be an exception under such circumstances.

Although the literature presents various definitions and measures of labor productivity. The productivity of labor in terms of agriculture, especially regarding agricultural extension, is elusive. As Hunt (2000) puts it;

> Labor productivity (also called returns to labor, and labor efficiency) is al-

> ways, and by definition , the product of a ratio. The numerator is some measure of output per unit area, and the denominator is some measure of labor input per unit area. Three concepts must be observed and measured before we have a figure for labor productivity: the unit area (usually acre or hectare), the output per unit area (usually volume or weight), and the labor input for that same unit area (usually hours or days of labor). Two conditions should be noted: (1) because the calculations are done per unit area, the relationship of this unit area to the operations of a farming household are not visible; and (2) merely stating the number of days of labor per unit area or per farm does not constitute a measure of labor productivity (p. 260).

Agriculture is a major employer of labor in developing countries especially in sub-Sahara Africa, employing the bulk of the population in many countries in the region (Gollin, Parente, and Rogerson, 2002). In an analysis of productivity patterns of some 62 developing countries in view of the agricultural transformation concept, Gollin, Parente, and Rogerson (2002) find that " $\cdots$ growth in agricultural productivity is quantitatively important in understanding the growth of GDP [gross domestic product] per worker for developing countries" (Gollin, Parente, and Rogerson (2002), p.163).

Similarly, Kostov and Lingard (2005) argues that the role of institutions and social capital in optimizing the full potential of agriculture, that the productivity of extension systems, especially extension workers, needs to be raised beyond present level.

Thus, the productivity of extension is a necessary condition to kick start the agricultural transformation process in sub-Sahara Africa in particular, and developing countries in general, in order to achieve economic growth (Diao, Hazell, Resnick, and Thurlow (2007); Birkhaeuser, Evenson, and Feder (1991); Betz (2009); Axinn and Thorat (1972); Van Campenhout (2013)).

2.5 Peer effects and social networks

Social networks comprise of social structures that consist of nodes which represent ties between individuals, groups or organizations that are bound by one or more specific kinds of interdependency. The interdependency may include beliefs, friendships, values, trade, or conflict. This can be depicted by complex graph-based structures (Bramoullé, Djebbari, and Fortin (2009), p.42). The literature on peer effects in relation to social networks is evolving. For instance, studies show that the actions, choices and outcomes of individuals in social interaction is usually a reflection of those of their peers (Cliff and Ord (1981); Cohen-Cole (2006); Cont and Bouchaud (2000); Fortin and Yazbeck (2011); Bikhchandani, Hirshleifer, and Welch (1992); Bikhchandani, Hirshleifer, and Welch (1998); Banerjee (1992); De Giorgi, Pellizzari, and Redaelli (2010); De Giorgi, Pellizzari, and Redaelli (2010); Mas and Moretti (2009); Bramoullé, Djebbari, and Fortin (2009); Manski (1993)).

Moreover, peer effects relate to the influence of social networks (Scott (2013); Wasserman and Galaskiewicz (1994)) and social interactions on behavior, attitudes, and accomplishments (such as academic performance or productivity at work) of individuals in a wide variety of social context. For example, recent studies show that the decision of students on which course major to specialize on (De Giorgi, Pellizzari, and Redaelli, 2010), and how their consumption of recreational facilities (Bramoullé, Djebbari, and Fortin, 2009) can be a function of the outcome of peers. Studies show that the performance of outputs workers tend to exhibit interdependence (Mas and Moretti (2009); Herries, Rees, and Zax (2003)), and generally, workers take their cues from peers when faced with making certain choices (Banerjee, 1992), such as financial decisions (Bursztyn, Ederer, Ferman, and Yuchtman (2012); Cont and Bouchaud (2000)).

Social network analysis provides a rich information for the identification of peer effects among economic agents such as community knowledge workers in the current study. However, identification is often a nuanced process. The challenge is to "identify what drives the correlation between outcomes of individuals who interact together" (Bramoullé, Djebbari, and Fortin (2009), p.41).

Manski (1993) observes that a major issue in the identification of peer effects applies to the inability of a researcher to clearly distinguish the direction of influence among interacting agents. Thus, in his piece - "The reflection problem" (Manski, 1993), shows that identification of peer effects in the context of a linear-in-means model is fraught with two main identification problems. First, serious difficulty abounds in distinguishing real social effects (i.e., endogenous/peer effects and exogenous effects) from correlated effects. Second, simultaneity in the outcome (such as performance) of individuals in social interaction leads to perfect collinearity between the expected average outcome of the peer group and its average characteristics. This occurs even when correlated effects are presumed absent. Hence "the reflection problem", which limits the potential of separating endogenous social effects (i.e., peer effects) from exogenous effects (Bramoullé, Djebbari, and Fortin (2009)). It implies that there is a joint probability for an individual's performance to be influenced by the average performance of his reference group as much as the possibility that the group's behavior may be influenced by the individual's own outcomes (Mas and Moretti (2009)).

Manski (1993) identifies three effects that are possible when individuals in social interaction tend to behave similarly. First, the endogenous effect refers to the propensity for an individual's behavior to co-vary with the mean behavior/outcome of the reference group. Second, the exogenous (contextual) effect refers to the propensity of the behavior of an individual to vary with the exogenous characteristics of his peer group. And third, the correlated effect connotes that individuals in the same group would tend to behave similarly due to similar individual characteristics or as a results of similar influential settings such as managerial or institutional factors (Manski (1993)).

Thus, Manski (1993) argues that the identification of peer effects within a social interaction context should be preceded by a careful analysis of, and quest for pertinent erstwhile information on the composition of the reference group. Absent such information, the chances for a plausible identification would depend on the population relationship between the variables in the peer groups and those that directly affect outcomes According to Manski (1993),

> ··· influence is difficult to impossible if these variables are functionally dependent or statistically independent; whereas the prospects are better if the variables defining reference groups and those directly affecting outcomes are only moderately related in the population (p. 532).

In a study on the financial decision making habits of people in the asset-pricing industry, Bursztyn, Ederer, Ferman, and Yuchtman (2012) conjectured that when someone purchases an asset, his peers may also want to purchase it, both because they learn from his choice (i.e. social learning) and because his possession of the asset directly affects others' utility of owning the same asset (i.e social utility). The analysis shows that both channels have statistically and economically significant effects on investment decisions. Peer effects were identified in investment decisions of agents. Such analysis provides information on how revealed preference could be decoupled from possession. Thus, Bursztyn, Ederer, Ferman, and Yuchtman (2012) surmise that peer effects exist in financial markets as well. They suggest that in some fields such as finance, it is important that a researcher goes beyond the mere identification of peer effects and try to identify why the choices of an individual are affected by his peers.

Mas and Moretti (2009) utilize a data set on the performance of checkers (cashiers) across a supermarket chain in the US to estimate peer effects in workers' productivity. All individuals in the study had similar work environments such as similar task (mainly scanning items and receiving payment from customers), using the same technology, and the same incentive scheme. Thus, correlated effects were assumed to be fixed (absent) among the total number of workers surveyed. The idea is consisted with Bramoullé, Djebbari, and

Fortin (2009) and Manski (1993) whose research settings preclude any form of correlated effects among subjects. Mas and Moretti (2009) wanted to investigate how workers in a team react to an exogenous change in the productivity of their coworkers when peer effects are present, and in the absence of peer effects. They find that the return to introducing a highly productive worker into a group is greater than his/her individual contribution when working alone. They also find that strong peer effects are associated with the introduction of highly productive workers into work groups, and that the effect was strongly correlated with spatial interactions (represented by a worker's line of sight of vision) (Mas and Moretti, 2009).

Further, Mas and Moretti (2009) show that through positive peer effects, workers influence one another in the context of productivity spillovers. They find that in the absence of peer effects, a worker exerts less efforts compared to what was exerted following the introduction of a highly productive coworker into a shift. That is, without peer effects, the marginal benefit of effort for each a worker declines as the effort of coworker's increases. However, peer pressure potentially mitigates such externalities. Therefore they infer that the marginal utility of effort exerted by a worker depends on that of coworkers. Hence, the mix of workers that maximizes productivity is the one that maximizes the diversity of skill within a network Mas and Moretti (2009). It implies that the overall productivity of a set of workers will be higher if high skill workers and low-skill workers are employed in the same shift (or in social network) compared to cases where some networks comprise only of high-skill workers and others of only of low-skill workers.

Bramoullé, Djebbari, and Fortin (2009) utilize advances in social network analysis to provide "easy-to-check necessary and sufficient conditions for identification [of peer effects]" (Bramoullé, Djebbari, and Fortin (2009), p.42). Using the US adolescent (i.e., add health) data set to estimate the consumption of recreational services by secondary school students, Bramoullé, Djebbari, and Fortin (2009) utilize the empirical abstractions of social networks and the linear-in-means model to group students into social networks. Thus, on the basis of the three propositions of Manski (1993) regarding the identification of peer effects, Bramoullé, Djebbari, and Fortin (2009) find that through social networks analysis, endogenous and exogenous social effects could be identified with plausibility. Further, they show that such result could predict the existence or absence of peer effects. Bramoullé, Djebbari, and Fortin (2009) conjectured that by segregating students into different groups and assuming the absence of correlated effects, the consumption of recreational activities by an individual student in a social group may be affected by the mean recreational activities of the group containing the individual as well as that of his/her friends (peers). Further, Bramoullé, Djebbari, and Fortin (2009) find that depending on the nature of a network, peer effects and exogenous effects are generally identified under network interaction. Thus, it is possible to disentangle endogenous and exogenous social effects through social networks (Bramoullé, Djebbari, and Fortin (2009)).

Sacerdote (2001) also finds positive peer effects among college roommates in at Dartmouth college in the US. The analysis utilizes the random allocation of new (entering) students into dorms and to roommates. By measuring a reduced-form equation that captures the effects of the background of individual students on that of their peers, Sacerdote (2001) suggests that randomness in allocation prevents correlated effects among peers. Regression analysis on the individual grade point average (GPA) records of students shows that roommate peer influences are important in freshmen year GPA and in decisions to join social organizations (Sacerdote (2001), P.702).

Another study (Jain and Kapoor (2013)) considers the impact of formal and informal business school peers on academic achievement of students in a Master of Business Administration (MBA) program in India. In order to disentangle peer effects, they randomly assign students into two kinds of groups: 1. study groups and 2. residential groups. The two groups were classified as formal and informal groups respectively. They find that informal residential peer groups have a significant impact on academic performance, whilst the formal study groups had a negligible impact on the academic performance of students. They also find that weaker students benefit disproportionately more from heterogeneous peers compared to their stronger colleagues.

Munshi (2003) empirically investigates the existence of positive peer effects (through social networks) among Mexican migrants and how individual migrants from a sample of individuals who belonged to multiple origins in various Mexican communities in the US over a long period of time influence each the employment decisions and prospects of one another. An analysis of migration data on the patterns and labor market outcomes aimed at identifying job networks among Mexican migrants in the US labor market show positive social network effects in the labor market outcomes of Mexican immigrant workers (Munshi, 2003). Thus, individuals who belong to wider networks have greater probability of being employed in high paying jobs as compared to those who do not (Munshi, 2003).

Two similar studies, Hanushek, Kain, Markman, and Rivkin (2001) and Markman, Hanushek, Kain, and Rivkin (2003) identify peer effects among students by observing that peer influences cause students to make schooling decisions that contrast with their revealed abilities. By analyzing data on students in their first job after graduation, it was possible to estimate the effect of different major decision modes on wages and on the (self-reported) probability of job mismatch. In particular, they find that students who chose a major following their peers, and in contrast to their revealed ability, graduate with lower final grade points averages, end up in lower paid jobs, and are more likely to be mismatched (Hanushek, Kain, Markman, and Rivkin (2001); Markman, Hanushek, Kain, and Rivkin (2003)).

In agriculture, studies on peer effects have mainly tended towards technology adoption among farmers in a social interaction (Foster and Rosenzweig, 1995). For instance, Bandiera and Rasul (2006) use an agricultural technology adoption data on the adoption of sun flower in Mozambique to determine whether and how the adoption decisions of a new technology by a specific farmer depends on the adoption decision of other farmers in his/her social networks (or community). They conjectured that since farmers have high propensity to share information with one another, a particular farmer would be more likely to adopt when he knows many other farmers that have adopted. However, counter-intuitively, Bandiera and Rasul (2006) find that "the marginal benefit of knowing one more adopter is positive when the farmer knows few other adopters, while it becomes negative when the farmer knows many other adopters" (p.3).

Thus, Bandiera and Rasul (2006) show that peer effects are highly visible in the adoption decisions of farmers, in that the probability of a farmer adopting a technology decreases with the number of his peers that have adopted in the short run. Such inference was based on observing that

> ⋯ knowing many adopters could cause a farmer to strategically delay adoption in order to free-ride on the information obtained by his peers. Hence the adoption relationships of farmers in relation to their peers that have adopted, corresponds to an inverse-U relationship (Bandiera and Rasul (2006)).

Similarly, Liverpool-Tasie and Winter-Nelson (2012) analyze the significance of social networks in technology adoption among peasant farm households in Ethiopia. The goal was to determine whether networks in the rural areas make any contributions to the adoption of technology, whether social learning occurs in networks, and to determine if social learning has a functional relationship with network types. They use the target input model (which describes the relationship between the rate of input use by a farmer as a consequence of his acquired information/technological adoption, and the resulting output) to study social learning among farmers in relation to agricultural technology adoption. They find that social learning is highest with a technology that exhibits the most visible of outcomes. On the other hand, a technology that do not show visible outcomes produces less social learning and peer effects. For example, peer effects were highest on technology associated with irrigation on vegetables and pulses compared to the other forms of technology transfer (see Liverpool-Tasie and Winter-Nelson (2012)).

Moreover, as in Bandiera and Rasul (2006), Liverpool-Tasie and Winter-Nelson (2012) find that an *inverse-U* relationship exists between technology adoption and the number (network) of a potential adopter's friends. They also suggest that social learning due to network effects, is strongest in networks (or social connections) that are based on intentional relationships compared to those social connections that are merely through proximity (or neighborhoods).

In a similar study on social learning through social networks, Krishnan and Patnam (2014) analyzed panel data on farm households in Ethiopia to study agricultural technology adoption (of fertilizer and improved seeds) among rural households. They compared the impact of farmer's adoption decision, the role of social learning between farmers (peers effect) and learning from extension agents. They find that peer effects between farmers was stronger compared to learning from extension agents, in the diffusion (and adoption) of agricultural technologies among farmers. Krishnan and Patnam (2014) employed the linear-in-means model[2] and exploited the empirical application in Bramoullé, Djebbari, and Fortin (2009) as well as applications of spatial auto-regression to identify positive and significant peer effects (and social learning) among farmers in Ethiopia as regards technology adoption. In comparison to learning from extension agents in the same setting, Krishnan and Patnam (2014) show that technology adoption was more influenced by the effects of farmer-peers on peers than the effects of learning from extension workers. Thus, they surmise that social learning (peer effects) is a very potent force in the adoption and diffusion of a new agricultural technology (Krishnan and Patnam, 2014)

[2]Cohen-Cole (2006) call the linear-in-means model the "workhorse of the social interactions analysis"

2.6 Spatial econometrics and social network analysis: The link

Spatial econometrics is closely linked to the identification of peer effects (also called endogenous social effects) through the applications of social network analysis (Bramoullé, Djebbari, and Fortin (2009); Cohen-Cole (2006); Durlauf and Ioannides (2010); Scott (2013); Lee (2007); Kostov and Lingard (2005); De Giorgi, Pellizzari, and Redaelli (2010); Krishnan and Patnam (2014)) and conformity (Bernheim (1994); Beugnot, Fortin, Lacroix, and Villeval (2013); Bernasco, de Graaff, Rouwendal, and Steenbeek (2012); Jackson (2005); Kostov and Lingard (2005); Manski (1993); Topa (2001)).

Spatial econometrics has a pronounced attention and research applicability in economics generally through the increasing use of spatial and social network data (e.g., Anselin (2010); Case (1991); Anselin, Bera, Florax, and Yoon (1996); Anselin (1990); Bell and Dalton (2006); Bertrand, Luttmer, and Mullainathan (2000); Baltagi and Liu (2011)). Fischer (1996) defines spatial data analysis in a broader context, as the statistical study of phenomena across space. Such analysis relies on certain concepts such as the coordinates of points (i.e, location in space), topology, distance, area, spatial arrangement, as well as spatial interaction between or among agents. Spatial analysis draws heavily on what is referred to as *the first law of geography*, which posits that "everything is related to everything else, but near things are more related than distant things" (Fischer (1996)).

Spatial analysis rests on two important issues: - the absolute location of objects or agents (i.e., spatial location, also referred to as coordinates points) and the relative location (known as spatial arrangement) of objects or agents. Moreover, spatial location breeds two kinds of spatial effects: - 1). spatial dependence (also known as spatial autocorrelation), and 2). spatial heterogeneity (Fischer (1996); Anselin (1988)). Both issues have serious implications for social network data. For instance the use of spatial weights matrix, usually specified as W to denote the specification of a neighborhood structure and the analysis of spatial data sets (Fischer, 1996). The matrix W has elements $w_{i,j} = 0$ when agents i and j are not neighbors; and $w_{i,j} \neq 0$, otherwise. Thus, spatial analysis usually involves computation of observed values at individual locations and the spatial lags (W_Y) (i.e., the weighted average of observations or outcomes) of neighbors (Fischer (1996)).

Thus, the application of spatial econometrics in studies of peer or neighborhood effects and other pertinent economic studies, is becoming prominent. For instance, Gravelle, Santos, and Siciliani (2013) used spatial econometrics to determine whether the quality of a hospital can be affected by the quality of services provided by other hospitals (in its sphere of competition). They apply spatial econometric methods to a sample of English hospitals in $2009 - 2010$ with a set of 16-quality measures (including mortality rates, readmission, revision and redo rates and three patient reported indicators) to determine if a hospital will have a higher quality when its rivals have higher quality or not. By constructing a theoretical model with regulated prices which specify conditions on demand and cost functions, they find that a hospital's quality is positively related to the quality of its rivals for seven out of the sixteen quality measures across the hospitals. Further, they suggest that for every ten percent increase in quality of rivals, a hospital shows a corresponding increase of 1.7% - 2.9% in the quality (see Gravelle, Santos, and Siciliani (2013)).

Case (1991) utilized spatial patterns to estimate household demands for rice in 141 districts across 11 provinces in Indonesia. She posits that under certain circumstances, it could be best to include the use of both spatial effect models and fixed effect models for estimating spatial patterns. Specifically, she estimates a log function of the quantity of market rice purchased by a household (Y) against key variables of interest such as the log of household expenditure per household (ln XPC), the size of the household, and more. She also conducts a test of spatial correlation using the Moran's I index. She finds that spatial econometrics models are very expedient in cases where group (such as district) specific effects are uncorrelated with the regressors. Thus

> The spatial modeling approach is relevant for a wide range of issues. In public finance, for example, spatial modeling can be used to suggest the extent to which states or nations look to others in determining the appropriate composition of taxes or tariffs, level of expenditure, and public good provision. Research on the effect of networking within urban areas may find spatial techniques useful in identifying externalities associated with unemployment or poverty in inner cities. [And] the extent to which changes in firm behavior are matched by competitors can also be also be studied using spatial techniques, where data can be used to determine both the identity of competitors (W), and the extent to which correlated behavior is the result of intentional copycatting (Φ), or simply the result of common shocks (Case (1991), p.964).

2.7 The position of this study in the extant literature

As mentioned in the introductory section (i.e., chapter 1), my research contributes to the literature in three specific ways. First, it is unprecedented in its attempt to identify peer effects in the performance of extension workers with the intent of making inferences and recommendations that could improve agricultural extension systems in developing countries, especially in sub-Sahara Africa.

Two recent studies: Liverpool-Tasie and Winter-Nelson (2012) (wherein the impact of extension visits on farmers' productivity was compared with that of social learning among farmers in the context of social networks, on the agricultural technology adoption decision of farmers) and Krishnan and Patnam (2014) (wherein the effects of peers on the adoption decision of farmers was contrasted with extension through the effects of information received directly from extension agents); both provide rigorous impact assessment of extension services using social network analysis and techniques in spatial econometrics.

However, both studies (i.e., Liverpool-Tasie and Winter-Nelson (2012) and Krishnan and Patnam (2014)) do not focus on peer effects among the extension workers themselves, in terms of their own productivity (or performance). Moreover, I am not aware of any study on peer effects in the performance of extension generally, especially with regards to the performance of extension workers in group interaction.

The present analysis pioneers the process of filling this gap by identifying and estimating peer effects among CKWs in rural Uganda on the basis of an agent-to-agent relationship. Moreover, this study is to the best of my knowledge, the first to study a key parameter of the extension systems i.e., the actual labor productivity (in terms of performance) of extension workers. Many previous studies have taken a holistic or black box approach to studying the impact of extension in diverse settings. Viewing the sector as a black box fails to provide meaningful guide to the achievement of efficiency in extension systems. For instance, Gautam and Anderson (1999) suggest that due diligence is required in empirical analyses pertaining to measuring the impact of extension.

Van Campenhout (2013) attempts to identify the relevance of the CKW model in Uganda from the perspective of farmers who receive extension services delivered by CKWs. However, the analysis only aims at identifying the impact of the dissemination of information by CKWs through the search app. He used a difference-in-difference technique to gauge the impact of the CKW model by considering as key parameters, knowledge, attitudes, practices and outcomes to farmers as a result of their interactions with CKWs. He finds that, although significant impact was attributable to CKW intervention through reported increased technical knowledge among farmers regarding cropping (generally with regards to agronomic techniques such as spacing manure/organic matter application) and increased market information among farmers in treated areas, there was no way of disentangling the impact of CKWs from the treatment and untreated areas. That study also fails to identify the actual impact of CKW services on the level of improved knowledge gained by farmers in respect of their agricultural production in general.

Due to the problem of lack of direct attribution of agricultural productivity to the contribution of extension systems, there should be alternative measures of gauging the contribution of extension, through the performance of extension workers. This study thus, attempts to fill this gap by using social network analysis to start the process of attributing value to extension through peer effects.

Chapter 3

Research methodology

This chapter presents a detailed outline of the methods applied in this study. It also comprise of sections that describe the study area, the data (in terms of the data generation process and sampling), and a set of theoretical and structural models which provide the basis of the econometric and identification strategies utilized in this study.

3.1 Background description of the study area and research context

Uganda is in the eastern part of Africa, below the the Sahel deserts. It is situated across the equator about 800 kilometers inland from the Indian Ocean. The country is landlocked, and situated between latitude 290°34 East and longitudes 350° South. It is bounded on the North-East by Sudan and Kenya respectively, while its South and Western neighbors are Tanzania and Democratic Republic of Congo (DRC) respectively. The total area is 241,550.7 square kilometers, of which the land area comprise makes up about 199,807.4 square kilometers. The population is estimated at about 35 million with annual growth rate of 3.2%. Fertility rate is a high of 7 with life expectancy at birth estimated at 50 years (UBOS, 2013b)[1]. The country is divided into 56 districts which are sub-divided into lower administrative units including counties, sub-counties, parishes and villages (also referred to as Local Council 1 (LC 1)). Figure 3.1 shows the map of Uganda.

[1]Note that UBOS means Uganda Bureau of Statistics

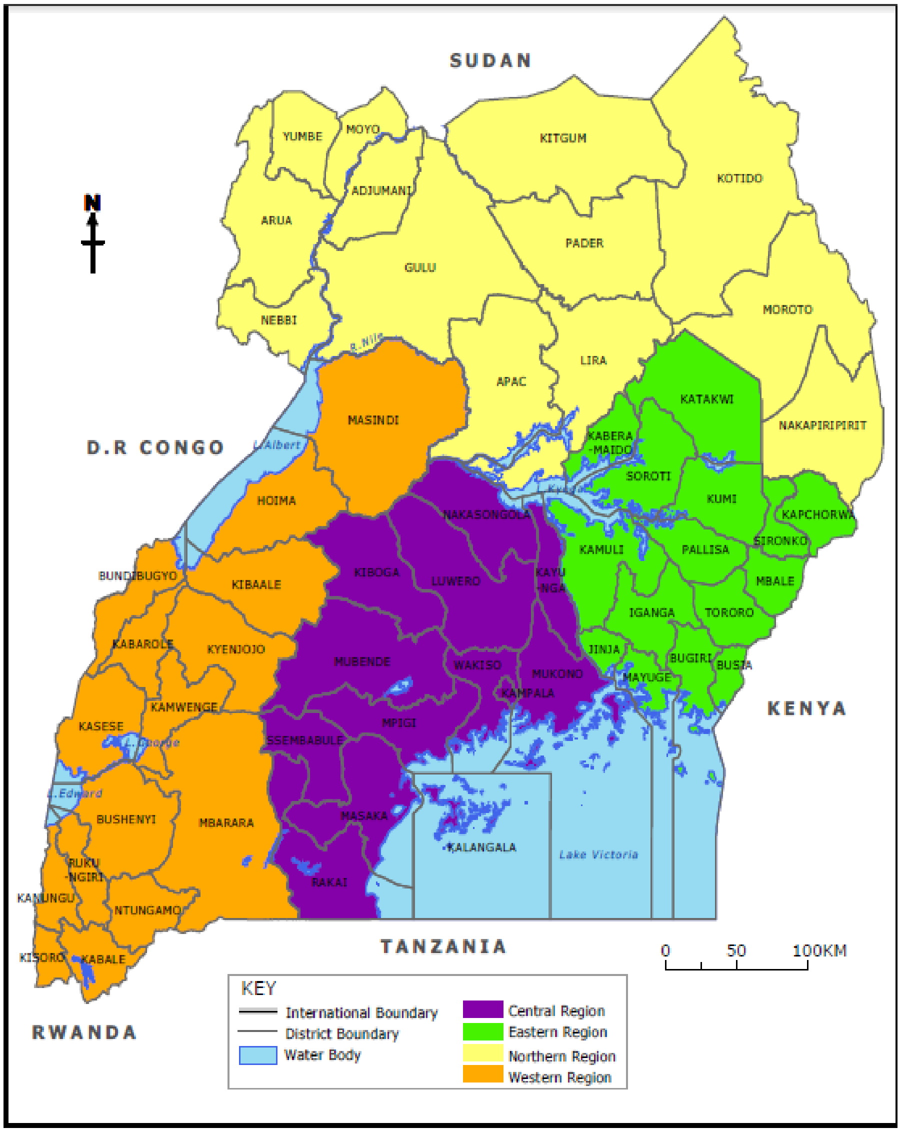


Figure 3.1: Map of Uganda

CKWs work at the parish level in the districts. In the 2002 census, a total of 5,238 parishes were reported across the country. The average population size of a parish is a little over 6000 persons. The country's population is about 35 million people, with more than half of the population (56%) comprising about 19.3 million, are engaged in farming (McCole, Culbertson, Suvedi, and McNamara, 2014).

3.1.1 The agricultural context of Uganda

Since Uganda is landlocked, local food production is a natural tendency due to constraints with importation. Most of the food production is aimed at household consumption (McCole, Culbertson, Suvedi, and McNamara, 2014). The economy is agrarian with agriculture accounting for about 66% of national employment. Moreover, agriculture's contribution to the country's gross domestic product (GDP) is around 22% (UBOS, 2013b). Export earnings in the form of raw materials, comprise of about 40%, with coffee, tobacco and fish being the main export commodities which provide much of the needed foreign exchange for the country (UBOS (2013b); UBOS (2013a); Muto (2012); Muto and Yamano (2009); McCole, Culbertson, Suvedi, and McNamara (2014)). The main food crops comprise of bananas and plantains, some cereals (including rice, maize, millet and sorghum), as well as legumes (including groundnut, soybean and sesame) (UBOS, 2013b).

The introduction of ICTs in Uganda has recently started to generate immense benefits for the country in terms of its agricultural production. For instance, Muto and Yamano (2009) observe that the production and distribution of banana, the country's staple crop is on the increase in terms of the proportion of households involved in the marketing of the crop in rural communities as a result of the use of cellphone technology. The availability of cellphone coverages to rural communities has caused an increase in the proportion of households who sold banana from 43% in 2003 to about 68% in 2005 (Muto and Yamano, 2009). Moreover, the proportion of banana sales to banana production increased by 11.2% in those rural communities (Muto and Yamano (2009)).

Poor transportation infrastructure in the rural communities poses a problem of transporting farm produce to markets. For example, figure 3.2 shows several bunches of banana on a bicycle, depicting how the crop is often transported to markets.

Source: Grameen CKW pilot report, 2010

Figure 3.2: Bicycle as the main form of banana transportation in rural Uganda

3.2 Description of the community knowledge worker (CKW) program

The community knowledge worker (CKW) program started in Uganda as a pilot project by Grameen foundation - an affiliate of Grameen bank (of Bangladeshi Nobel Laureate, Mohammad Yunus). The program is implemented as a technology innovation and monitored directly by a unit called Grameen Application lab (APLAB). That unit is responsible for developing, gathering, and testing new innovations in line with applicability (or adaptability) to local conditions. The CKW Initiative was conceptualized on the premise that having a wide network of local extension staff across rural communities can use cellphone facilities to disseminate vital agricultural information to rural smallholder farmers, thereby improving livelihoods in those communities.

The goal of the CKW program is to improve the livelihoods of smallholder farmers (most of whom are very poor), through improved access to agriculture information. The agricultural information is delivered by a select group of community members from each district.

Prior to the CKW program, agricultural extension and advisory services (EAS) were extremely low in the country with over 85% of rural farmers lacking any kind of extension support from the government extension workers. However, CKWs currently serve over 50% of all rural farmers in the country (McCole, Culbertson, Suvedi, and McNamara, 2014). Poor transportation infrastructure significantly hinder the supply of traditional extension services since travel to remote communities (such as villages and communities across hilly terrains) constitutes a daunting task for most government extension workers. Further many public agencies that hitherto provided EAS in Uganda grappled with tough organizational challenges in reaching poor farmers McCole, Culbertson, Suvedi, and McNamara (2014).

Moreover, the national agricultural advisory services (NAADS), which had been particularly in charge of agricultural extension in Uganda since 2001, recently became incapable of delivering basic services due to diverse issues such as financial mismanagement (through embezzlement) and public policy uncertainties (McCole, Culbertson, Suvedi, and McNamara (2014)). This made the farmer-to-extension worker ratio very high McCole, Culbertson, Suvedi, and McNamara (2014).

The program was initiated with a planning grant from the Bill and Melinda Gates foundation. The grant was used to implement a nine-month "Test of Concept" or a Pilot phase, which began in December 2008 in Uganda implemented by Grameen APLAB. The goal of the pilot was to provide answers to key questions on farmers' productivity by testing and further development and refinement of the CKW model. The aim was to provide strategic insight into how to effectively mainstream the project. The pilot phase lasted in August 2009. During the period, Grameen APLAB conducted a mix of several activities such as prototyping mobile information services and conducting agricultural surveys using cellphones among other forms of ICT.

Currently, the number of CKWs has grown considerably from the original number recruited (i.e., 40) at the program's inception, to as many as 1,139 (by June 2013,) working across 39 districts in Uganda compared to less than 10 districts in 2010. Further, they have conducted about 1,144,771 successful queries (information searches) for farmers, and completed 69,603 relevant surveys (McCole, Culbertson, Suvedi, and McNamara (2014)) compared to 14,000 and 6,000 respectively during the pilot phase.

The selection of a CKW is usually done by Grameen in consultation with community members, through community representatives at the parish level in every district. Each CKW is nominated by members of his/her own community based on a set of criteria such as experience and commitment towards farming, credibility, and integrity. Nominees are screened by Grameen foundation prior to being recruited, first as trainees, and subsequently as CKWs, to work across a set of communities (usually within a parish). As a prerequisite, CKWs are committed and serious farmers who are respected in respective their communities.

The emphasis on community involvement in the recruitment of CKWs by attesting to, and verifying their capacity for agricultural and community services within their communities (most times in their respective parishes or neighboring parishes in their districts), makes it justifiable to refer to them as community knowledge workers.

The idea of the CKW program was inspired by lessons from a preceding program - community health workers initiative, which was successfully implemented in Uganda wherein members of rural communities were chosen to become providers of basic health and medical care to their communities (Van Campenhout (2013)).

Most CKWs take advantage of the opportunity for improved farming through the wealth of information at their finger tips (being conduits of the agricultural information in their CKW-program cellphones) to implement agriculture at a more advanced and satisfactory level for themselves and their families using their acquired knowledge and information. That is, a typical CKW tries to "practice what he preaches" by improving on his previous farming activities using the knowledge and information privilege he has as an extension agent, but at the same time, a local, full - time farmer. This serves as an additional incentive for working as a CKW. For instance, figure 3.3 shows a CKW as an example of a smallholder farmer using improved farming technology to raise livestock.

Figure 3.3: A CKW proudly showing his livestock as an exemplary smallholder farmer

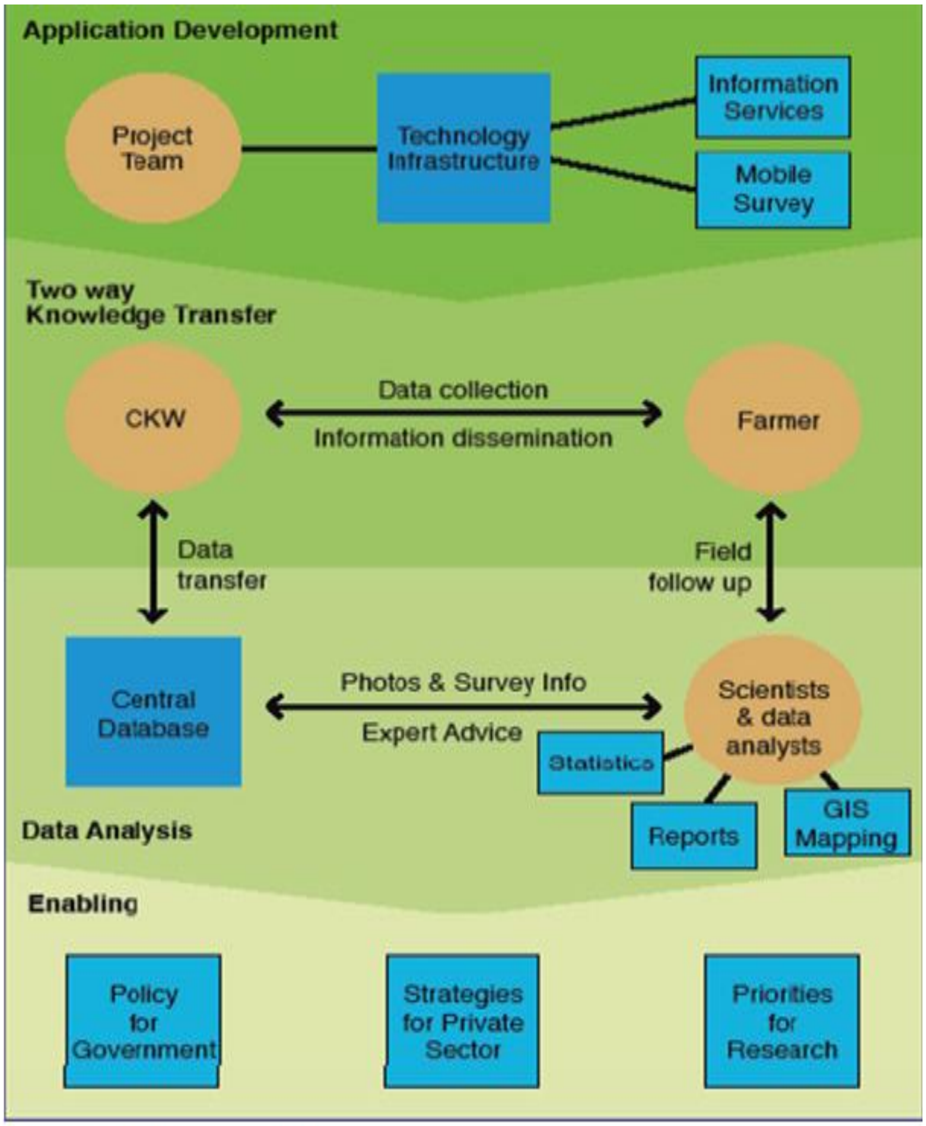
3.2.1 Operational description of the CKW model

The CKW program relies mainly on the use of cellphones (smartphones) as a tool to provide improved agricultural knowledge and information to smallholder farmers. Such innovative knowledge and information, which is often centralized in universities and research stations, usually inaccessible to smallholder farmers, are made accessible to them through CKWs who reside among these smallholder farming communities.

Thus, CKWs are branded as *feet in the field* since they serve as local conduits of critical agricultural information. CKWs are also effective representatives of the local farmers. They serve as intermediaries between farmers and research stations and institutions, by acting as channels of smallholder farmers' concerns to research institutions (excerpts from the CKW pilot report, 2010).

The CKW model involves knowledge brokerage, albeit the farmers are not charged for the services. The model could be understood as a schematic framework or process which starts with application development wherein Grameen APLAB develops new ideas, and also gathers new technology from research stations around the world and transmits that knowledge or innovation to local farmers through the technology infrastructure which comprise of the android cellphones and apps used by CKWs. In turn, CKWs gather information about farmers' agricultural concerns and transmit it to Grameen APLAB for improvement.

Figures 3.4 presents the CKW model in Uganda in a schematic form, showing the various linkages in the operations system of the program.



Source: CKW Pilot report, 2010.

Figure 3.4: The CKW operational model

The CKW program has since been implemented in strategic partnerships with local agricultural institutions including the Ministry of Agriculture. CKW program is also in partnership with the main cellular service provider in the country - MTN-Uganda. About 40 CKWs were initially recruited for the pilot. These were trained and became trainers of future CKWs trainees as the program expanded to different parts Uganda. It is reported that the initial total amount of surveys conducted by CKWs was about 6,000, and as many as 14,000 searches were conducted for smallholder farmers.

The program is monitored by Grameen foundation and its partners. Strict monitoring and evaluation of program activities lend credence to outcomes and help to identify problems in a nascent stage. Thus, Grameen APLAB instituted a monitoring mechanism for the performance of CKWs during the initial phase of the program. The process involves an early compilation of a farmers database (by asking CKWs to collect demographic data on their clientele farmers). There is also a customized dashboard which is used by Grameen APLAB (at the headquarters in Kampala) to track CKW activities on a regular basis. Such information serves as a basis for evaluating the performance of these CKWs. It also serves to provide up-to-date information on the extent of the reach (or coverage) of the program.

Due to partnership with MTN-Uganda, the CKW outfit (and logo) comprises a yellow-colored background, with an inscription of a CKW using cellphone with one hand, and holding hoe on the other hand. This inscription is meant to demonstrate the main goal of the program, which is agricultural production through the intervention of cellphone technology (see McCole, Culbertson, Suvedi, and McNamara (2014); Van Campenhout (2013)).

Figure 3.5 shows a CKW wearing the official CKW uniform (which exhibits the CKW symbol) and holding the official CKW smartphone. The symbols on the uniform in figure 3.5 can be explained thus: The yellow color is the main symbol of the cellphone company (i.e., MTN-Uganda) which underwrites the provision of uninterrupted cellular coverage to CKW operational areas in Uganda. The person holding the hoe represents the smallholder farming community CKWs serve, while the cellphone represents the synergy between ICT and local farming ideas, especially pertaining to smallholder agriculture.

Figure 3.5: A CKW depicting the CKW model through the uniform and cellphone

3.2.2 CKW training program and implementation of knowledge brokerage through farmers' groups

Two recent studies - McCole, Culbertson, Suvedi, and McNamara (2014); and Van Campenhout (2013), provide a detailed information on the aspect of CKW training and operation in Uganda. CKWs are usually trained in batches of about 50, which involves 2 different classes of about 25 students in each batch. It is reported that CKW - trainings are usually intensive and lasts for about 10 -12 hours per day for up to 4 days per section. The language of instruction for CKW trainings is English since the agricultural database in the cellphones is encrypted in English. Some of the issues addressed in the each training include a detailed introduction and background of the CKW program, highlighting key aspects of the program's philosophy and operational dynamics such as the value proposition of the program, participants expectations during training as well as their responsibilities after training. Each CKW is provided with accommodation during the training, as well as a travel grant to cover meals and incidentals (McCole, Culbertson, Suvedi, and McNamara (2014)).

A major part of the CKW operation entails the training of farmers, usually in groups, as shown in figure 3.6 below. Aside from the one-to-one provision of information for farmers through the process of searching the agricultural database in the cellphones, CKWs usually take time to train farmers in groups, on how to better carry out farm operations.

Training of farmers' groups enhances mutual trust between CKWs and farmers as farmers get to ask questions in groups and CKWs address their farming concerns. Moreover, some of the members of farmers' groups can later become CKWs depending on their level of understanding and performance in their communities.

Source: Grameen CKW pilot, 2010

Figure 3.6: A CKW training farmers on farming principles

Moreover, The delivery of trainings and other critical agricultural information services to farmers in groups may help ensure sustainability of the program by determining (mostly through feedback from group members) how the program is rolled out and sustained across different communities.

3.2.3 The CKW operational (working) environment

Most of the farmers in the CKW operational areas are very poor. They are mostly elderly folks who are left behind to take care of plantations and other farming operations, as the younger, more energetic youths migrate to the Urban areas of the countries (such as Kampala city) in search of better livelihoods.

The situation in rural Uganda in terms of rural -urban migration, is consistent with many rural settings in the developing world, especially within sub-Sahara Africa where social amenities are often lacking in rural areas. It is also believed that through the CKW program, rural-urban migration may be curtailed.

Figure 3.7 shows the researcher and a CKW visiting with an aged farmer in his home within a mountain-coffee plantation (background) in the study area.

Moreover, CKWs often work across coarse terrains that comprise of hills and mountains. Like figure 3.7, figures 3.8 and 3.9 show hilly terrains which consists of a key area of the CKW work environment (Several districts in Uganda, such as Kasese and Gulu are very hilly and mountainous). Such environments present huge transaction costs to CKWs and farmers.

In particular, aged farmers who reside and undertake farming activities in such intractable terrains mostly rely heavily on CKWs to aid their farm operations through the supply of critical information such as those pertaining to weather and prices in nearby markets.

Figure 3.7: A visit with a farmer in one of the hilly terrains

Source: Author, using Grameen CKW data.

Figure 3.8: A view of CKW work environment - hilly terrains

Figure 3.9: A view of CKW work environment - Another view of hilly terrains

The work of CKWs across these rough terrains further justify the relevance of the CKW program, since CKWs are regarded as the *feet in the field* for these farmers in terms of the supply of critical farming information such as weather and market information for their crops.

3.2.4 The CKW working equipment

A key aspect of CKW training involves familiarity with the use of an android smartphone, and a ready-set, which constitutes the main operational equipment for their activities. The CKW operational cellphones contain the CKW platform (including the search, farmer registration, and survey apps). Hands-on experiences are fostered in each training, usually through rigorous exercises and practices focused on the program operation. Selected CKWs get an operational toolkit (comprised of the ready-set) for field work.

The ready-set provides vital support functions for the cellphones by supplying power to charge the CKW's phone as well as the cellphones of community members for a small fee, which constitutes an extra stream of income for CKWs. The ready-set also serves as a source of electricity (power) for lighting CKWs' homes. Thus, the ready-set is extremely vital for CKW operations in the communities. Periodic refresher trainings are usually conducted throughout the year depending on program needs.

The ready-set consists of a battery and a connection to a solar panel which is normally fixed on the roof of a CKW's dwelling where it can receive solar energy from the sun. However, the ready-set is relatively mobile. That means, the CKW can move it in and out of their homes in search of better sunlight so that it can receive more solar energy in any given day.

Figures 3.10 through 3.12 show a CKW describing the ready-set to researcher.

Figure 3.10: Researcher study the ready-set battery

Figure 3.11: Researcher observing the ready-set battery

Figure 3.12: Researcher holding (and observing) the solar panel of the ready-set

3.3 Data

Data for this analysis obtains from administrative monthly records of CKW performances as shown by their total monthly searches[2] over the period, December 2010 - December 2011. This period coincides with an incentive realignment for CKW performance. Using these monthly records, I construct a spatial panel for regression analysis.

The data comprise of a compilation of the total monthly performance records for CKWs over 13 months covering the period December 2010 to December 2011. In order to induce higher performance by CKWs, Grameen realigned the incentive scheme in June 2011. The monthly remunerations were raised by 50% across the board for top categories of performance from 40,000 Ugandan shillings (UGX40,000) to 60,000 shillings (UGX60,000) for a monthly performance corresponding to a grade of A for topmost performance[3]. performance. The goal was to induce higher performance among CKWs as the program was being rolled out to many districts.

3.3.1 Data generating process

Grameen foundation utilizes an ICT system that records the daily performance record of each CKW. The system automatically generates and stores these records on a server called *sales force* which constitutes the central operating system for monitoring Grameen CKW operation in Uganda. The system is directly supervised by staff at the Grameen headquarters in Kampala on a daily basis. Each *search* that a CKW makes for a farmer generates a *query* which is automatically captured and encrypted in *sales force*. The phones used by CKWs

[2]The basis of CKW operation requires that CKWs look-up (*search*) and identify solutions to a farmer's problem from the pre-installed agricultural database in their project cellphone. The information includes commodity market prices in the nearest centers from a farmer, instruction on livestock and crop disease management, and more

[3]topmost performance that corresponds to a grade of A (i.e., if the total number of a CKW's monthly search is at least 48). The next two grades are *B, C and D* which correspond to monthly performance of 47-35, 34-23, and 23 or fewer searches respectively

is designed to send each performance record by automatically generating every query in the *sales force* and stored in the *cloud*. Daily performance records of each CKW are recorded with the corresponding geocodes, the farmers' identification numbers (IDs), and the time of the of the entry. This process ensures that CKW extensional operations are effectively monitored. It helps to prevent problems of human errors which might be associated with manual recording of performance records by Grameen staff at the headquarters.

3.3.2 Sample size

I restrict the analysis to a sample of CKWs with appropriate identification numbers (i.e., person IDs) and available geocodes (values for longitude and latitude). I select a total of 650 CKWs for the analysis. I then construct a K-Nearest neighbor interaction matrix (i.e., weight matrix) based on the 5 -nearest neighbors of any CKW (i.e., $K = 5$. Thus, it is a 5NN weights matrix) within the network comprising of the entire set of districts. The use of cellphones by CKWs as the primary means of operation by CKWs in this setting makes it plausible to extend interactions among CKWs beyond specific district levels. I assume that both intra-district and inter-district interactions are possible in the setting due to the means by which CKW operations are done. The use of cellphones as the main tool for CKW operations enhances interactions among CKW both within and across districts [4]. Thus, I argue that intransitive triads are plausible in the research setting.

Figure 3.13 shows a geographic information systems (GIS) map of the districts from which the sample was selected.

[4] This is different from other studies of peer effects where interactions between agents are strictly within an isolated geographic structure such as a school or village

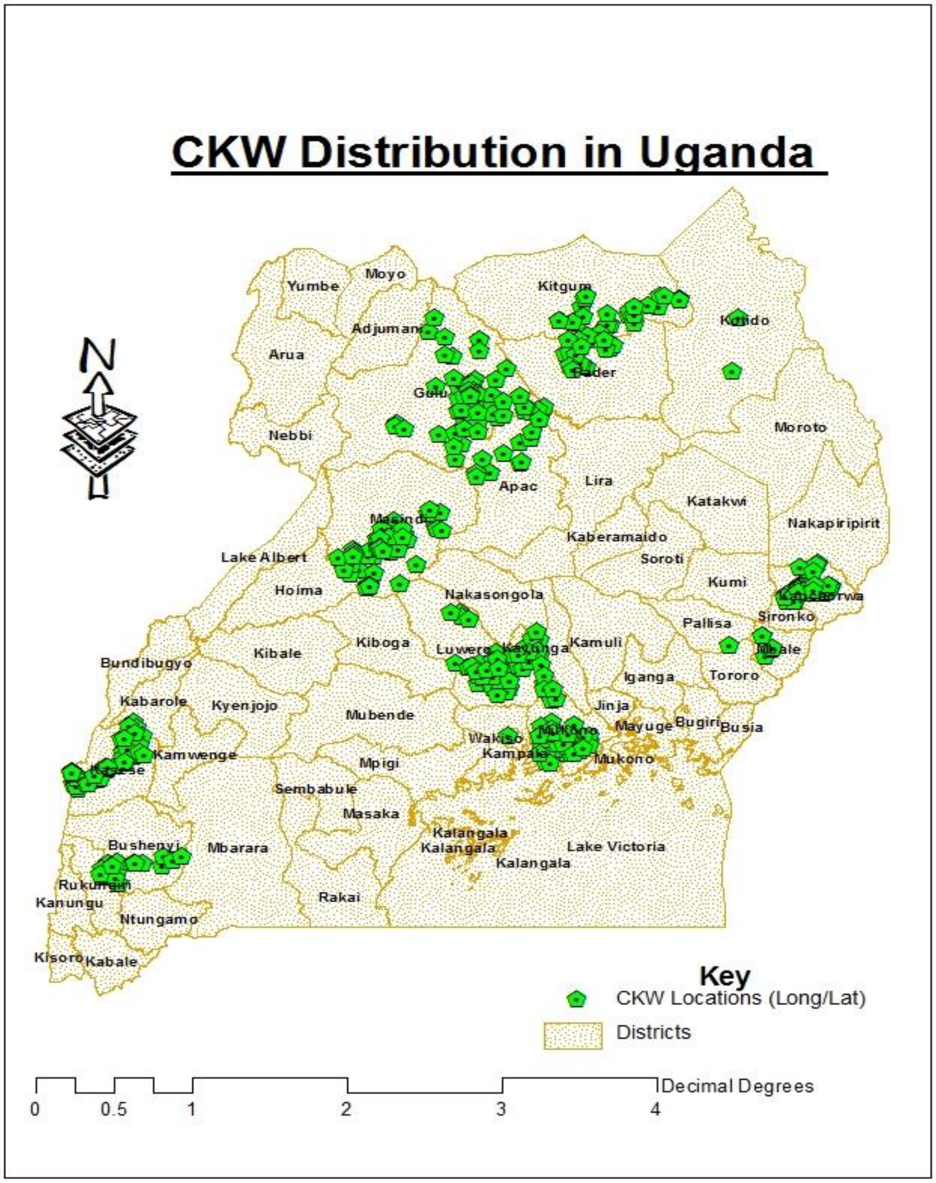


Figure 3.13: CKW distribution map in Uganda

3.4 Econometric strategy

In a linear-in-means model, the identification of peer effects on the total monthly performance of an individual CKW within the context of social interaction is a nuanced process. Endogeneity in the performance of peers resulting from simultaneity in peer interactions often creates difficulty in the identification of peer effects. This is the reflection problem discussed by Manski (1993).

However, advances in social network analysis such as Moffitt (2001); Cohen-Cole (2006), provide rich methodologies to adjust the linear-in-means model and obtain the identification of peer effects. For instances, Bramoullé, Djebbari, and Fortin (2009) show that an extension of the linear-in-means model separates peer effects from those of social interaction by separating the endogenous effects from exogenous effects. The analysis relaxes the assumption of group interactions among peers in a social networks setting (Bramoullé, Djebbari, and Fortin, 2009). Bramoullé, Djebbari, and Fortin (2009) empirically use this approach on the US adolescents health (Ad health) data set to identify peer effects in the consumption of recreational services among young adults in 2009.

The method has become popular for studies on peer effects in divers settings including those pertaining to agriculture. For example, Krishnan and Patnam (2014) use it to separate the effects of extension services on the adoption of agricultural technology in Ethiopia, from the peer effects among farmers in the same setting. Similarly, De Giorgi, Pellizzari, and Redaelli (2010) apply the approach to identify peer effects among college students in a University setting in Italy. Further, Fortin and Yazbeck (2011) use the methodology on the add health data set to identify peer effects in weight gain among US adolescents.

3.4.1 Theoretical model

The theoretical model for this analysis carefully follows the theoretical model of Bramoullé, Djebbari, and Fortin (2009). It consists of a stylized version of the linear-in-means model to disentangle peer effects (i.e endogenous social effects)from exogenous social effects in the context of social network analysis (Bramoullé, Djebbari, and Fortin, 2009). The approach solves the reflection problem identified by Manski (1993). I posit that each individual extension worker (i.e., CKW) has a peer group whose average performance and characteristics influence his own outcome. I represent vectors by bold, lower case letters, and matrices by capital letters. For a set of CKWs i, (i = *1*, ...,n); $\mathbf{y}_i$ represents the total monthly performance (measured by the total number of searches recorded per month). $\mathbf{x}_i = 1 \times k$ vector of characteristics of i. Peer groups are CKW-specific. Thus, each i, belongs to a particular peer group P_i, with size, n_i. Moreover, a peer group contains all CKWs whose monthly performance or background characteristics may affect the total monthly performance of i.

I consider each district as a local network (with constituent of peer groups) in which interactions are structured among CKWs. The network of districts are partially overlapping in that a CKW i in district "A" might interact with any CKW j in district "B". A CKW i is excluded in the computation of the mean (average) total monthly performance of his/her peers. Specifically, $i \notin P_i$. i.e., each CKW is excluded from the peer group averages, P_i.

Three kinds of outcomes are consistent with this model. First, there is endogenous social effect - wherein the total monthly performance (y_i) of each CKW is influenced by the average monthly performance of his peers. This is known as the influence of peers on peers. Second, there is exogenous (contextual) effect - wherein the total monthly performance of each CKW is influenced by the mean (average) characteristics of his peers (i.e., peer characteristics). Third, there is correlated effect - the influence of a common institutional factor on peers. For instance, the effectiveness of the cellphones and the equipment (*ready-sets*) supplied to CKWs by Grameen APLAB might determine the total monthly performance of a particular set of CKWs. For instance, if CKWs in district A receive better functional cellphones and equipment than their counterparts in district B, then total performance in district B will lag behind that of district A.

From the theoretical model, there are divers ways by which the effects of peers could be communicated in the context of CKW operations in the this setting. For one, individual CKWs can learn from one another through information exchange on the cellphones they use for their work activities, about how to optimize their performance in order to get the highest monthly remuneration. Moreover, CKWs might benefit from information from peers (or neighbors) about the best approach to reach more farmers, or how to better operate their working equipment (such as during rainy seasons when the ready-set often malfunction due to contact with rain water).

3.4.2 Structural model

The structural model proceed thus;

$$y_i = \alpha + \beta \frac{\sum\limits_{j \in P_i} y_j}{n_i} + \gamma x_i + \delta \frac{\sum\limits_{j \in P_i} x_j}{n_i} + \epsilon_i, \qquad E[\epsilon|\mathbf{x}] = 0. \tag{3.1}$$

Where β captures the endogenous effect; δ is the exogenous effect. It is standard to assume that $|\beta| < 1$ ϵ_i reflects unobservable characteristics in the model. The regressors are strictly exogenous. i.e., $E[\epsilon|x] = 0$, where x_i is an $n \times 1$ vector of individual CKW characteristics (such as age, gender and marital status). Hence, I assume no correlated effects in this setting. Moreover, I use the standard assumption that for all j in J, the characteristics of individuals are similar (or common) in each network of neighborhood peers. Thus, all x_{ij} will be equated to x_j (Cohen-Cole (2006)).

The matrix version of the structural equation gives;

$$y = \alpha\iota + \beta Gy + \gamma x + \delta Gx + \epsilon, \qquad E[\epsilon|x] = 0, \tag{3.2}$$

Where y is an $n \times 1$ vector of the total monthly performance of individual CKWs for the entire network l; ι is an $n \times 1$ vector of ones; x is an $n \times k$ vector of observed own characteristics of individual CKWs; G is an $n \times n$ interaction matrix (i.e., weights matrix) representing the relationship between any two CKWs, wherein $G_{ij} = \frac{1}{n\,i}$ if CKW i is a peer of j, and 0 otherwise. This equation is a spatial auto-regressive (SAR) model with provision for an exogenous social effect term (i.e., δGx). Since $(I - \beta G)$ is invertible, the restricted reduced form equation follows thus;

$$y = \alpha(I - \beta G)^{-1}\iota + \alpha(I - \beta G)^{-1}(\gamma I + \delta G)x + (I - \beta G)^{-1}\epsilon. \tag{3.3}$$

I assume heteroscedasticity in the variance of the error term, and also that errors are independently and identically determined (iid).

3.5 Identification strategy

The strategy for identification of peer effects in this setting is based on a concept known as *intransitive triads*, which comprises of the existence of unsymmetric relationships between individuals within a network (Bramoullé, Djebbari, and Fortin (2009); Scott (2013); Wasserman and Faust (1994)). This is also referred to as "partially overlapping peers" (De Giorgi, Pellizzari, and Redaelli, 2010). For example, given a set of three CKWs: i, j, k wherein j affects i and k affects j, but not i; then, i,j,k comprise an intransitive triad for any i when $j = i - 1$, and $k = i - 2$. Geometrically,

$$G_{ij} = \left\{ \begin{array}{ll} 1, & j = i - 1 \\ 0, & j \neq i - 1 \end{array} \right\} \tag{3.4}$$

According to Bramoullé, Djebbari, and Fortin (2009), identification of peer effects is mainly based on the property of this G-matrix. For example, consider a case where $\gamma\beta + \delta \neq 0$[5];

- If the matrices I, G and G^2 are linearly independent, then social effects are identifiable.
- If those matrices are not linearly independent, then identification will be impossible except an individual is isolated from the group.
- The first part holds with almost any arbitrary G, and part II holds with any row normalized G.
- If this condition holds, then in the spirit of instrument variables, (G^2x, G^3x, $\cdots$) will be used as valid identifying instruments for the parameters in the network (Bramoullé, Djebbari, and Fortin (2009)).
- CKWs interact in peer groups.
- If the peer groups are symmetric, (i.e, all CKWs have the same number of peers), identification may not be possible.
- However, if at least two peer groups have different sizes, and that $\gamma\beta + \delta \neq 0$, then identification would be possible (Bramoullé, Djebbari, and Fortin (2009); Cohen-Cole (2006)).
- I argue that individuals in this setting do not have the same number of peers. Thus, it is possible to obtain identification.

[5]see propositions 1 and 2 in Bramoullé, Djebbari, and Fortin (2009)

3.5.1 Instrument variables for the identification challenge

Although this stylized version of the linear-in-means model leads to the identification and estimation of exogenous and endogenous effects of peers separately (Bramoullé, Djebbari, and Fortin (2009)), the effects of the average performance of peers in social interaction is endogenous. In other words, simultaneity in the outcome of peers within a network results to endogeneity in the effects of the average outcomes (i.e., total monthly performance in this setting) of peers (of CKWs) as peers face similar effects (Manski, 1993). This could result to biased estimate of the endogenous social effect (i.e., peer effects) due to omitted variable bias in the estimation process and present a serious challenge to identification (Wooldridge (2010a); Wooldridge (2010b)). Another potential challenge to the identification of peer effects in the total monthly performance of extension workers in the context of social networks is the potential for peer group formation to be endogenous. For example, it might be possible that social networks in this setting are formed because higher performing CKWs seek to establish interaction with other CKWs of similar performance. This selection bias might lead to bias estimates of the peer effects if it not accounted for (Manski, 1993).

Thus, the estimation strategy requires the use of instrument variables for the possible correlation between the total monthly performance of CKW peers in the same peer group within the network as well as selection bias in peer group formation. Kelejian and Prucha (1998) proposed a generalized two-staged least square (G2SLS) approach with an instrument set to correct for endogeneity. The approach has been used widely in the literature (e.g Bramoullé, Djebbari, and Fortin (2009); Krishnan and Patnam (2014); Lee (2007); Tan and Netessine (2012)).

The G2SLS method corrects for endogeneity by using the reported average characteristics of peers of peers (or neighbors of neighbors) as the set of identifying instruments for the mean outcome of peers. In the language of panel data econometrics, this simply implies using the lags of the own characteristics of peers (or neighbor) as valid identifying instruments (see Bramoullé, Djebbari, and Fortin (2009)). Moreover, 2SLS estimator provides consistent estimates while avoiding the problems of computational accuracy associated with the use of Maximum likelihood approach (Tan and Netessine (2012); Krishnan and Patnam (2014)).

To be valid, an instrument variable must satisfy the conditions of relevance and exclusion restriction. In other words, a valid instrument should be correlated with the endogenous regressors (i.e., relevant) but uncorrelated with the error term in the model (i.e., exclusion restriction) (Tan and Netessine (2012)). Thus, in this study, I justify the validity of the instruments by using the means of individual characteristics of overlapping peers, which are exogenous and are correlated with the average monthly performance of individual CKWs. Therefore, I argue that G^2x satisfies the exclusion-restriction condition for the validity of the instruments in this setting, and can represent the average performance of CKW peers (see Wooldridge (2010a)). The implication is that the observed characteristics of peers of peers can only affect the performance level of an individual CKW through the mean performance of his peers (See for example, Bramoullé, Djebbari, and Fortin (2009)).

For the computation, I multiply the interaction matrix between a CKW and his peers by itself resulting to the mean of exogenous individual characteristics of peers of peers (i.e the partially overlapping peers of peers). This implies that, G^2x can be used as a valid set of instruments for Gy, where Gy comprise of the observed characteristics of overlapping peers of CKWs in the network (see Bramoullé, Djebbari, and Fortin (2009); Lee (2007); Manski (1993)and Krishnan and Patnam (2014)).

Chapter 4

Estimation and data analysis

This chapter presents the estimation and analytic techniques for the data set. It provides descriptive statistics and graphical forms of description for the data such as the kernel density plots and Moran's scatterplots which provide information on the measure of variability of the total monthly performance of CKWs (dependent variable) in the research area.

4.1 Empirical strategy

I consider each of the 13 districts (l) as a small network with a stochastic but strictly exogenous interaction matrix G_l. I construct a block diagonal matrix (G) of the general network of all CKW districts and perform a local (within) transformation to G. Thus;

$$y(I - G) = \beta(I - G)Gy + (I - G)X\gamma + (I - G)GX\delta + \nu \tag{4.1}$$

Where X is the matrix of observations of the own characteristics of CKWs.
Individuals interactions are not exclusively in groups within the network of districts.
Thus, I, G, G^2, and G^3 are linearly independent[1].
Hence ((I -G)G^2X, (I -G)G^3X, $\cdots$) can be used as valid identifying instruments.

[1]from Proposition 4 of Bramoullé, Djebbari, and Fortin (2009)

4.1.1 Empirical equation

In order to estimate peer effects in CKW performance, I estimate the change in total monthly performance of each community knowledge worker (CKW) in the setting as a function of the number trainings received both during recruitment and afterwords. The use of training as the key explanatory variable stems from my desire to estimate performance of a CKW as a function of technical ability (i.e., technical knowledge about program operation) on the performance of individual CKWs (i.e., in terms of the number of searches done) per month. The standard literature on labor economics suggest that aside incentives and hourly or monthly pay (i.e., remuneration), the performance of workers in diverse settings is usually correlated with a particular set of variable(s) of influence. For example, training such as *On-the-Job-Training (OJT)* (De Grip and Sauermann (2013); Stern (1982)), workload (Tan and Netessine (2012)), and a stable work environment (Holland (1996)).

Preacher and Hayes (2008) provide a theoretical basis for the order of causation between an independent variable and a dependent variable whose effect is perceived to be transmitted through another variable known as a *mediating variable* (for example, *X, affects Y through M*). Thus, I estimate a linear model of the total monthly performance of CKWs, as a function of the number of training sessions they have attended. I control for the own characteristics and the average characteristics of peers (including district characteristics). I reproduce equation 3.1 with the general description of the variables follows:

$$\begin{split} Total\ monthly\ performance = \alpha_0 + \beta_1 Training + \sum_{k=1}^{n} Own\ characteristics\ \ + \\ \sum_{k=1}^{n} Parish\ \ characteristics + \sum_{k=1}^{n} District\ characteristics + \eta_{it} \end{split} \tag{4.2}$$

where η_{it} is error term.

I allow for peer effects among CKWs by incorporating spatial lag term of the number of searches (i.e., dependent variable) into the explanatory variables. I employ a panel data approach in this analysis. Specifically, I select a total of 650 CKWs from 13 districts[2] across rural Uganda were studies. I use the total monthly performance of each individual CKW during the period: December 2010 - December 2011. The panel produced a total of 8,450 observations for the analysis.

The dependent variable is total monthly performance over the 13-months' period. The right hand side variables include own characteristics of CKWs such as age, number of CKW training received, number of children, family size, amount of money owed as debt, and dummies for gender, marital status, attainment of secondary educational, whether a CKW works in a hilly terrain and more. Dummies = 1 if a case is positive, (e.g., if CKW is a male) and 0 otherwise. These are the controls specified in the functional model earlier. Some of these control variables, such as debt, dummy for hilly terrains affect the transaction cost of CKWs.

4.2 Data analysis and description

I employ a Generalized 2 - stage least square (G2SLS) to estimate the endogenous and exogenous social effects. The first stage involves estimating a 2SLS using as instruments;

$$S = [(I-G)X \quad (I-G)GX \quad (I-G)G^2X] \tag{4.3}$$

The model is over-identified and I obtain, as estimates;

- $\tilde{X} = [(I-G)Gy \quad (I-G)X \quad (I-G)G^2X]$ as the matrix of the explanatory variables.
- And $P = S(S'S)^{-1}S$ as the weighting matrix.

[2]See the list of districts in appendix

For the second step, I use

$$Z(\theta) = [E[I - G)Gy(\theta)|X, G] \quad (I - G)X \quad (I - G)GX] \tag{4.4}$$

This applies on the reduced form equation to yield;

- $[E[I - G)Gy(\theta)|X, G] = G(I - \beta G)^{-1}[(I - G)(X\gamma + GX\delta]$
- The model obtains identification of peer effects in the CKW performance.

Correlated unobservables are assumed to be absorbed. Hence I don't account for correlated effects in my analysis.

I compute the effects of peers on individual performance in two stages: first for the entire time span (December 2010 - December 2011), and second, for the time differences (i.e December 2010 - May 2011 on one hand, and June 2011 to December 2011 on the other hand). This time differential in peer effects helps to smooth out the effect of the incentive realignment. I consider total monthly performance as the dependent variable regressed on many explanatory variables to account for peer effects. The key explanatory variable is the technical knowledge acquired by of CKW proxied by number of trainings attended, and we control for CKW age, whether the CKW is head of his/her household, marital status, amount of money owed in debt, household size, the gender of CKWs, the number of children, and whether he works in a hilly terrain.

Further, I compute spatial lags for each interaction matrix. I apply a spatial-two-stage least square regression to account for the endogeneity of peer effects (Kelejian and Prucha, 1998) on the individual performance of community knowledge workers. The time period comprise of 13-months (i.e., December 2010 - December 2011). An incentive realignment occurred in June of June 2011, wherein the payment for achieving an "A" performance was changed by 50% (from 4000UGX to 6000UGX).

4.2.1 Measure of variability in CKW performance

A kernel density plot provides a good measure of variability in the dependent variable. This is vital for inferences to be made. Figure 4.1 presents a kernel density plot of the total monthly performance of community knowledge workers corresponding to the entire period consisting of the 13 months of the CKW operations.

Figure 4.1 shows that there is variability in the performance of these extension workers over the 13 months period. Figure 4.1 also shows that the performance of CKWs is not a normally distributed, but is skewed slightly beyond the mean. Some level of clustering at the peak performance values of performance, and a dispersion at lower levels of total monthly performance.

Since an incentive realignment (adjustment) occurred in the process of CKW operations during June 2011, one might wonder if there is variation in total monthly performance of CKWs across the two periods before and after the incentive adjustment. In order to compare the total monthly performance of these two periods (i.e., before and after separately) on either side of the incentive realignment, I construct the kernel density plots for both periods separately.

Figure 4.2 present a comparison of the total monthly CKW performance for these two periods which comprise of the before and after incentive realignment scenarios.

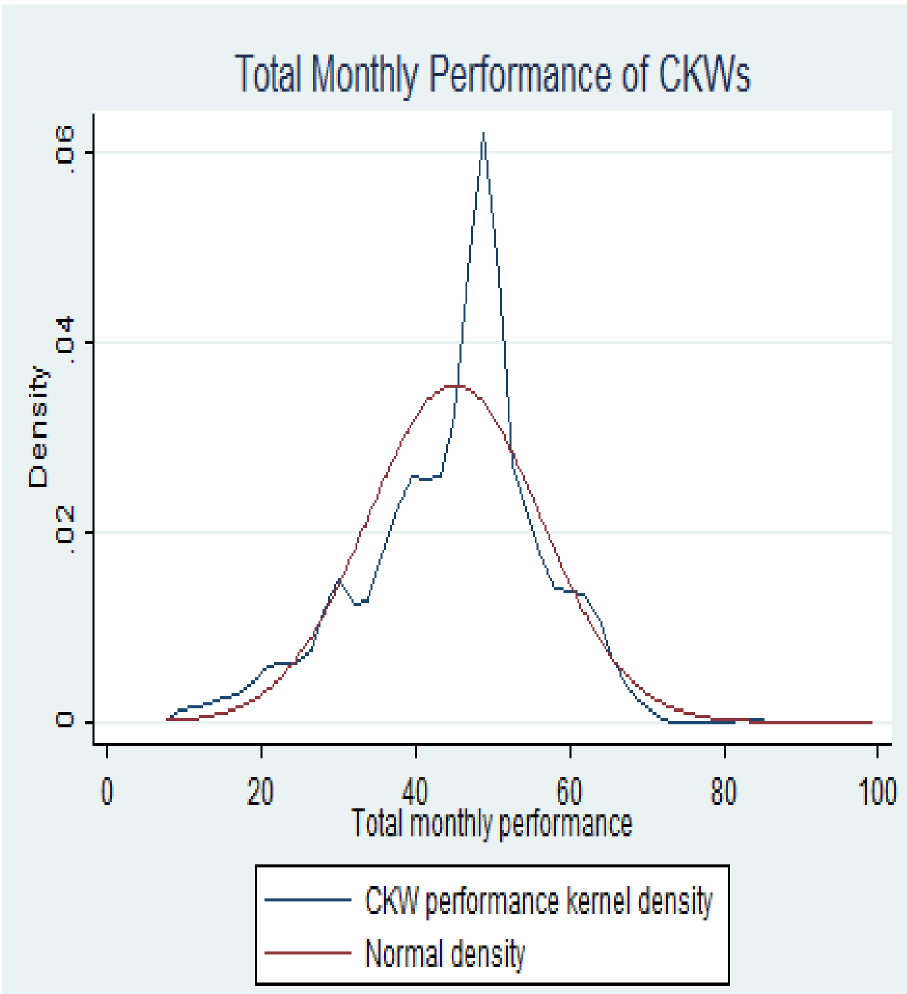


Figure 4.1: Kernel density graph showing CKW performance across time

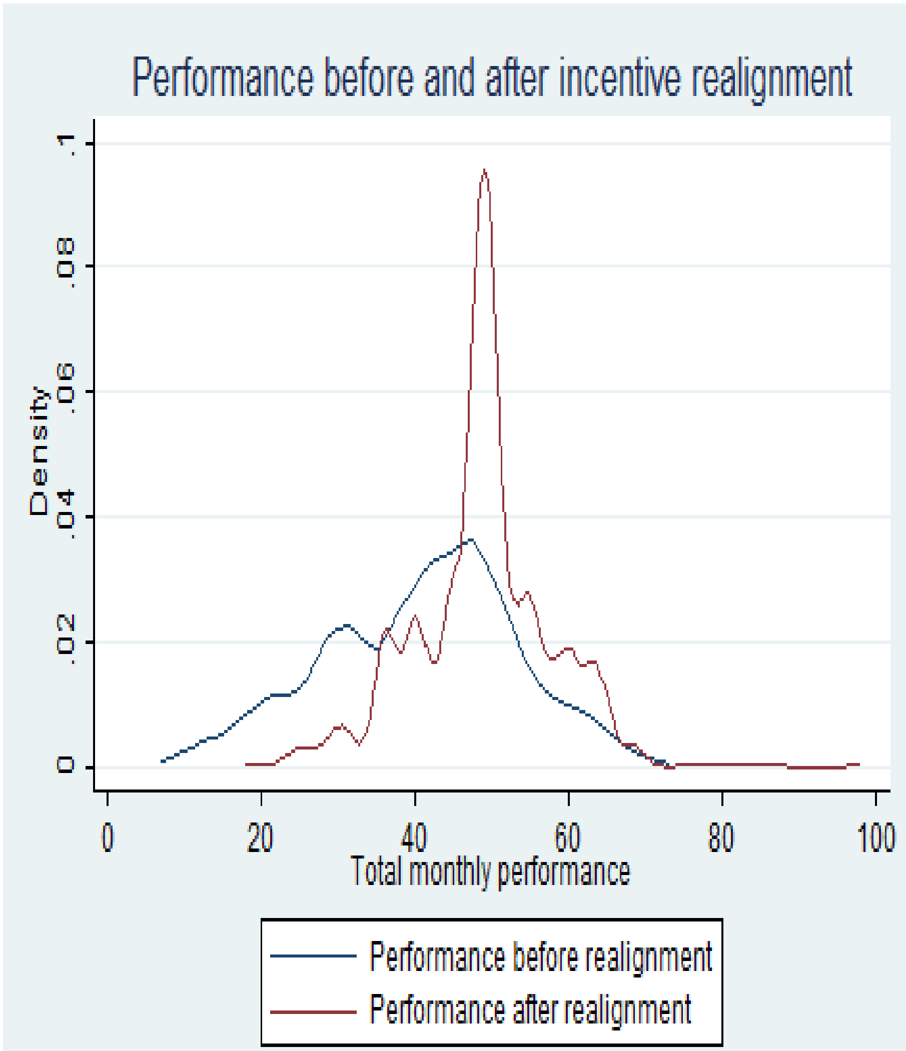


Figure 4.2: Kernel density graph comparing CKW performance before and after incentive realignment

Figure 4.2 shows that the total monthly performance of CKWs' corresponding to the period after the incentive realignment is much steeper than the performance attributable to the period before incentive was realigned. Figure 4.2 also shows that performance after incentive realignment tend to be clustered around the mean, whereas total monthly performance before the incentive realignment is somewhat spread (showing spatial dispersion).

4.3 Descriptive statistics

Table 4.1 presents descriptive statistics for the data. The distribution of community

Table 4.1: Descriptive statistics for entire period

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Total monthly performance	45.049	11.213	9	98
Age of CKW	36.537	10.709	18	67
Gender is male	0.688	0.463	0	1
No. of CKW Training	4.671	1.345	3	7
CKW is married	0.711	0.453	0	1
CKW is household head	0.752	0.432	0	1
Household size	6.385	1.788	1	10
No. of children	2.954	1.076	0	7
Works in hilly terrain	0.448	0.497	0	1
School in Parish	0.357	0.479	0	1
Clinic in Parish	0.626	0.484	0	1
Member of a farmers group	0.551	0.497	0	1
Market center in Parish	0.295	0.456	0	1
At least high school grad	0.872	0.334	0	1
Has a bicycle	0.452	0.498	0	1
Debt owed in USD	262.603	354.626	4	3624
Personal income in USD	239.871	435.623	8	6400
No breakdown of equipment	0.523	0.499	0	1
Crops, livestock and market search	0.468	0.499	0	1
CKW has other job	0.48	0.5	0	1
N		8450		

knowledge workers is not uniform across all districts. However, for this analysis, I select the same number of CKWs across the 13 districts under consideration in order to have balanced panel set of data. The number of observations (N) is 8450. The average age of community knowledge workers (CKWs) is 37. 69% of all CKWs are male, and in terms of marital status, 70% are married.

Moreover, 87% of all CKWs have at least high school education level. The average number of training sessions each CKW has attended is 5. This implies that one would expect a high level of performance among these CKWs probably as a result competence or confidence from attending more trainings. The average performance of CKWs, which is a measure of the number of monthly searches, is 45. This is 3 units below the threshold for an *A* performance (48 searches). Thus, the average performance is in the *B* range, which is generally acceptable as supported by the number of training.

45% of these CKWs own their own transportation. This transportation mainly comprise of bicycles and motorbikes, which are the popular means of transportation in the rural areas of Uganda. Bicycles are motorbikes are a very key in affecting the transactions cost of these community knowledge workers since public transportation is often lacking. Note that this bicycle ownership by individual CKWs is different from the bicycles supplied by Grameen foundation. Since Grameen does not supply bicycles to every CKW due to resource constraints, individual CKWs that already owned bicycles before joining the program definitely use it for both personal transportation and for their CKW operation work.

4.3.1 Spatial structure of total monthly performance of CKWs

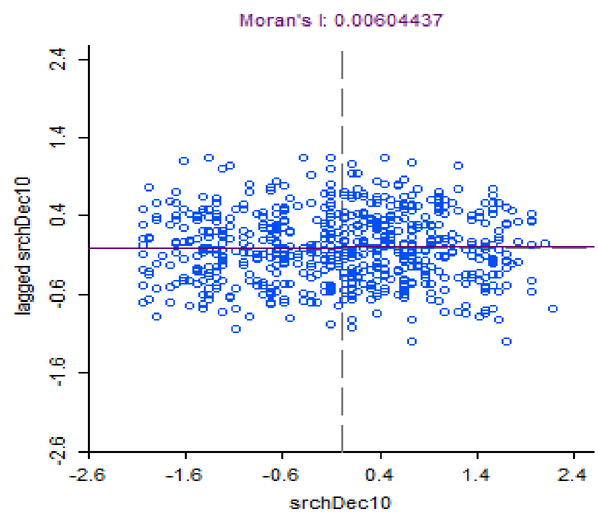
The basic test for spatial correlation is the Moran's I statistics (Case (1991)). Under the assumption that errors are independently and identically distributed, the values of the Morans I for the data indicates whether there is a randomness, dispersion or clustering in the total monthly performance of CKWs in rural Uganda. Moran's I values range between minus 1 and plus 1 (i.e - 1.0 and +1.0).

A Moran's I value closer to +1 indicates clustering in the monthly performance, whereas a value closer to -1 indicates dispersion, and a zero value indicates a completely random process (Anselin, Bera, Florax, and Yoon (1996); Anselin (2002); Anselin (2010)). Figures 4.3 through 4.9 presents the Moran's scatterplots for the monthly performance of CKWs. Performance is represented by the monthly searches made. The figures depict the spatial autocorrelation in the data regarding month CKW performance (in terms of randomness, clustering of dispersion) across the months.

Figures 4.3 through 4.9 show that CKW performance is characterized by very little (or somewhat average) levels of dispersion and clustering during the 13 - month period. This might be an indicator of the effects of peers in the entire network of districts since CKW performance neither tend to be completely clustered nor completely dispersed across the individual 13 months of the study period. At the same time, the Moran's scatterplots fail to confirm or negate the effects of realignment of the performance incentive that was done in the middle of the period (i.e June 2011). This further justifies the need to investigate whether peer effects exist in CKW performance in the research setting.

4.3.2 Local indicator of spatial association (LISA)

Moran's scatterplot for December 2010



Moran's scatterplot for January 2011

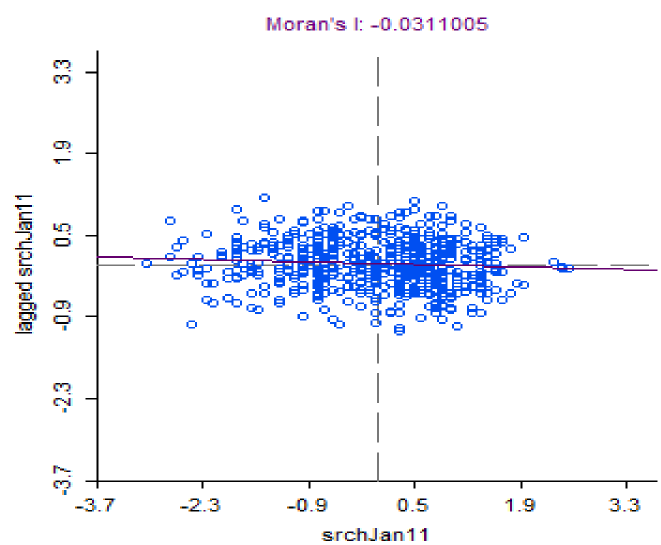
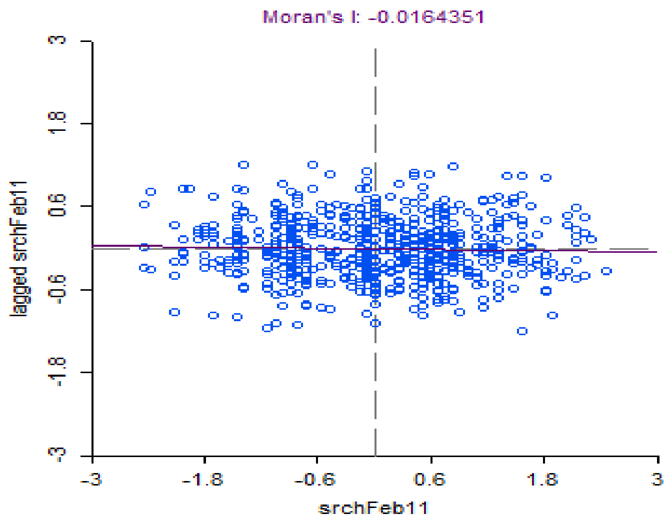


Figure 4.3: Moran's scatter plot for performance in December 2010 and January 2011

Moran's scatterplot for February 2011



Moran's scatterplot for March 2011

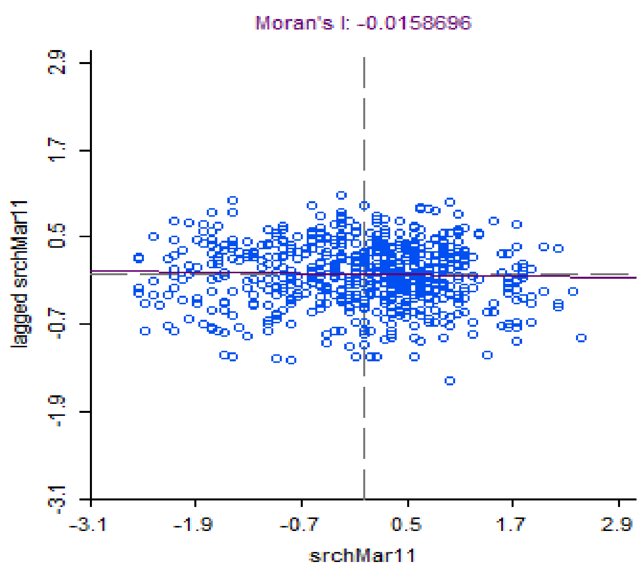
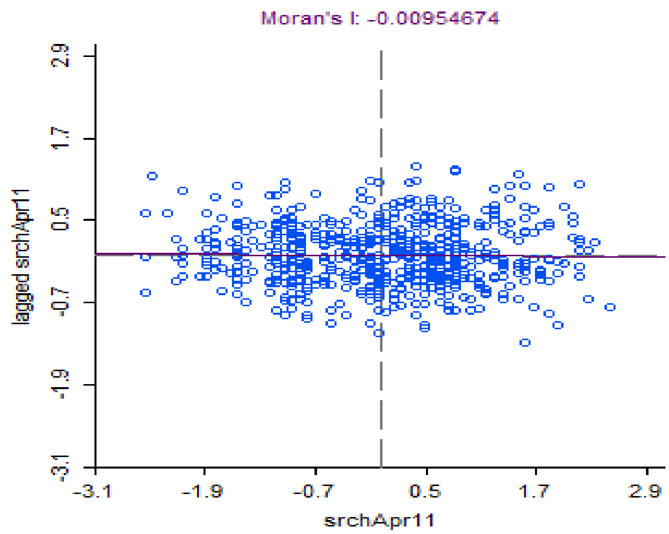


Figure 4.4: Moran's scatter plot for performance in February 2011 and March 2011

Moran's scatterplot for Apr 2011



Moran's scatterplot for May 2011

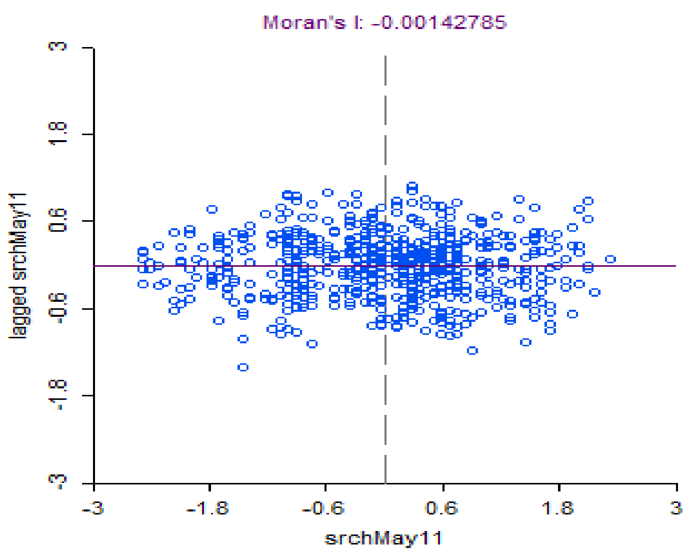
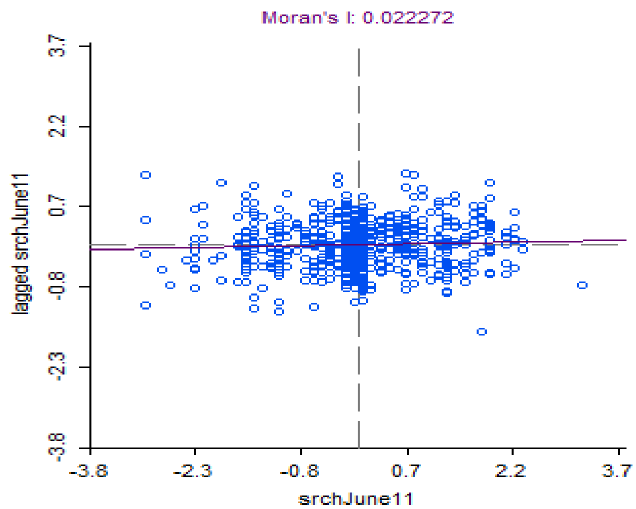


Figure 4.5: Moran's scatter plot for performance in April 2011 and May 2011

Moran's scatterplot for Jun 2011



Moran's scatterplot for July 2011

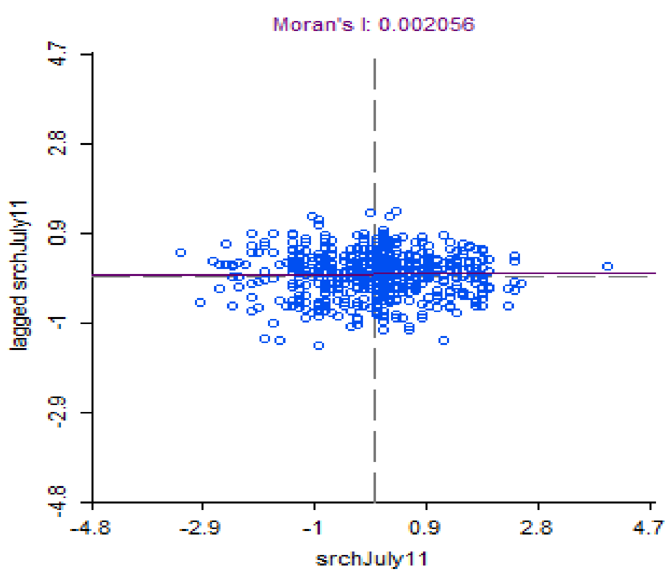
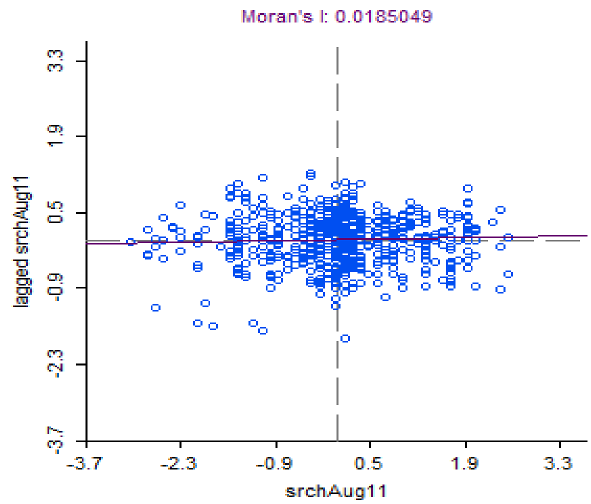


Figure 4.6: Moran's scatter plot for performance in June 2011 and July 2011

Moran's scatterplot for Aug 2011



Moran's scatterplot for September 2011

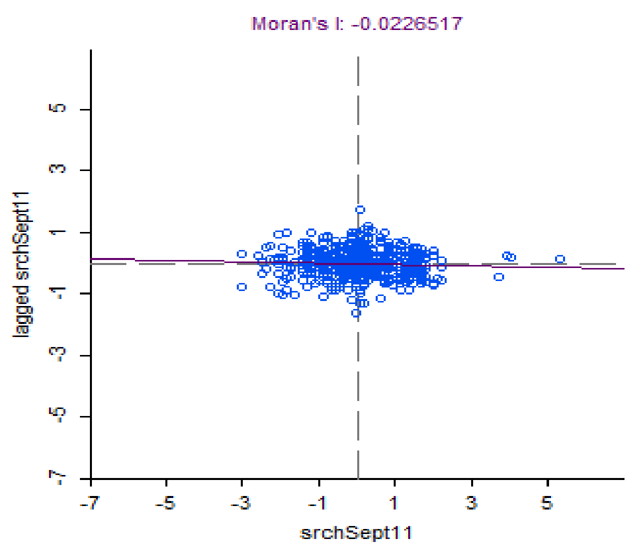
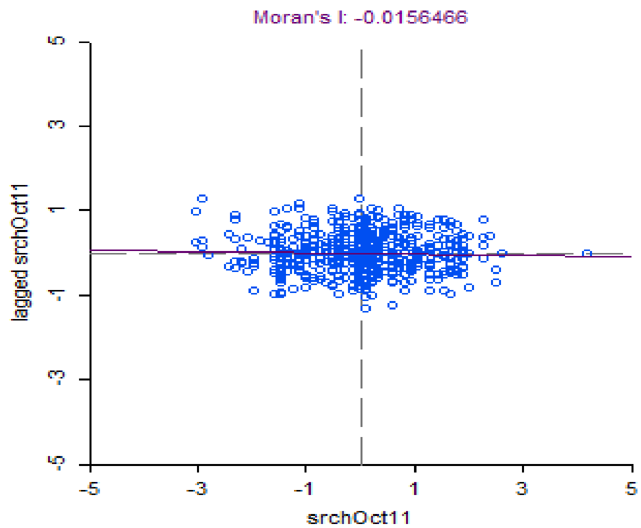


Figure 4.7: Moran's scatter plot for performance in August 2011 and Sept 2011

Moran's scatterplot for October 2011



Moran's scatterplot for November 2011

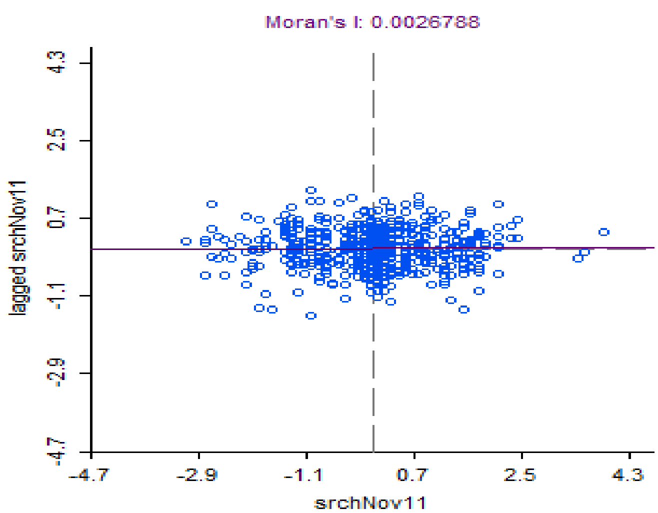


Figure 4.8: Moran's scatter plot for performance in Oct 2011 and Nov 2011

Moran's scatterplot for December 2011

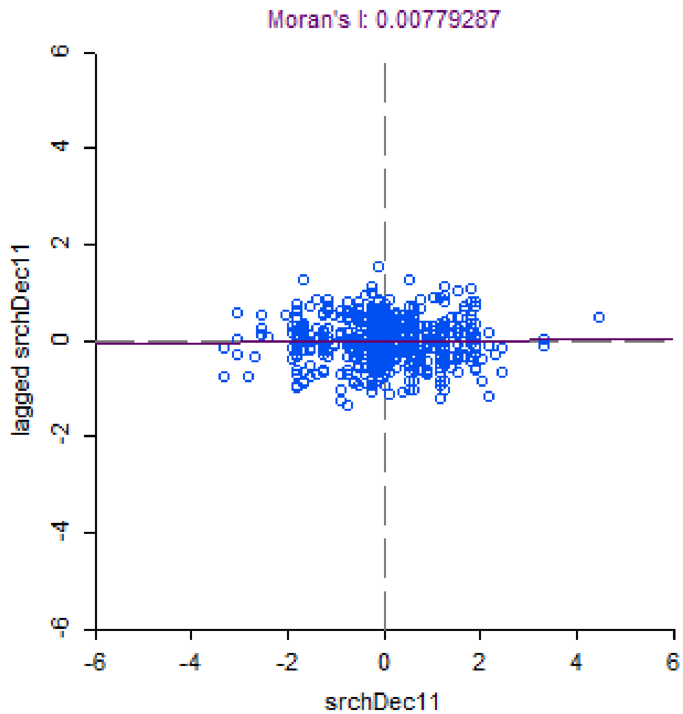


Figure 4.9: Moran's scatter plot for performance in December 2011

4.4 Descriptive statistics of data before and after incentive realignment

This section presents a comparison of the descriptive statistics in terms of performance, for the data on CKWs for the two periods before and after incentive realignment in June 2011. Table 4.2 reports the descriptive statistics (including mean, standard deviations, minimum and maximum) distributions for the data corresponding to the periods before incentive realignment, while table 4.3 shows data for the period after incentive realignment.

4.4.1 Summary statistics before incentive realignment

Here I present summary statistics of the performance data for the period before incentive realignment (adjustment). It comprise of the total monthly performance of individual CKWs for the period including December 2010 through May 2011. Table 4.2 reports the descriptive statistics (including mean, standard deviations, minimum and maximum) distributions for the data corresponding to the period before incentive realignment.

Table 4.2 shows that the number of observations corresponding to the period before incentive realignment is 3900. The average monthly performance is 41 searches. All the other variables are the same as those for the descriptive statistics corresponding to the entire period under consideration (i.e., before and after incentive realignment combined).

4.4.2 Summary statistics after incentive realignment

Here also, I present summary statistics of the performance data for the period after incentive realignment (adjustment). It comprise of the total monthly performance of individual CKWs for the period including June 2011 through December 2011. Table 4.3 reports

Table 4.2: Descriptive statistics before realignment

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Total monthly performance	40.844	12.341	9	71
Age of CKW	36.537	10.709	18	67
Gender is male	0.688	0.463	0	1
No. of CKW Training	4.671	1.345	3	7
CKW is married	0.711	0.453	0	1
CKW is household head	0.752	0.432	0	1
Household size	6.385	1.788	1	10
No. of children	2.954	1.076	0	7
Works in hilly terrain	0.448	0.497	0	1
School in Parish	0.357	0.479	0	1
Clinic in Parish	0.626	0.484	0	1
Member of a farmers group	0.551	0.497	0	1
Market center in Parish	0.295	0.456	0	1
At least high school grad	0.872	0.334	0	1
Has a bicycle	0.452	0.498	0	1
Debt owed in USD	262.603	354.65	4	3624
Personal income in USD	239.871	435.653	8	6400
No breakdown of equipment	0.523	0.5	0	1
Crops, livestock and market search	0.468	0.499	0	1
CKW has other job	0.48	0.5	0	1
N		3900		

the descriptive statistics (including mean, standard deviations, minimum and maximum) distributions for the data corresponding to this period.

Table 4.3: Descriptive statistics after realignment

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Total monthly performance	48.653	8.65	18	98
Age of CKW	36.537	10.709	18	67
Gender is male	0.688	0.463	0	1
No. of CKW Training	4.671	1.345	3	7
CKW is married	0.711	0.453	0	1
CKW is household head	0.752	0.432	0	1
Household size	6.385	1.788	1	10
No. of children	2.954	1.076	0	7
Works in hilly terrain	0.448	0.497	0	1
School in Parish	0.357	0.479	0	1
Clinic in Parish	0.626	0.484	0	1
Member of a farmers group	0.551	0.497	0	1
Market center in Parish	0.295	0.456	0	1
At least high school grad	0.872	0.334	0	1
Has a bicycle	0.452	0.498	0	1
Debt owed in USD	262.603	354.644	4	3624
Personal income in USD	239.871	435.645	8	6400
No breakdown of equipment	0.523	0.5	0	1
Crops, livestock and market search	0.468	0.499	0	1
CKW has other job	0.48	0.5	0	1
N		4550		

The number of observation corresponding to the period after incentive realignment is 4550. The average monthly performance is about 49 searches. All the other variables have the same interpretation as those for the period corresponding to the entire data set (i.e., before and after incentive realignment combined). Both table 4.2 and 4.3 show that performance is slightly higher in the period after incentive realignment, albeit the total number of month in this latter category is 7 as against 6 in the former. That might be responsible for the slight variation in both the number of observations and the total monthly performance figures.

Chapter 5

Results and discussion

In this chapter, I provide the result of the analysis. Through various robustness checks and regressions diagnostics, I show that my main results are plausible and consistent with the methods of social network analysis and peer effect identification. I first provide estimates of peer effects using the endogenous social effects as proxy variable for the entire data set including the total monthly CKW performance for the two periods before and after the incentive realignment time in June 2011 when the incentive for top performance was changed upwards by 50% (from 40000UGX to 60000UGX). Next, as a robustness check, I provide estimates of the two periods separately in order to determine whether there are peer effects in the two different periods (i.e., before and after). I also use various peer group definitions (or specifications) based on nearest neighbor matrices in order to determine the robustness of the main result.

5.1 Estimation result

This section provides the estimates of the main results of peer effects by applying the generalized two-stage least square estimation and spatial ordinary least squares (spatial OLS) to the stylized linear-in-means model that constitutes the econometric strategy of this analysis. The main result comprise of estimates of the endogenous social effects (i.e., peer effects), estimates of CKWs' own characteristics (in terms of how those characteristics impact the total monthly performance of a CKW), and estimates of the exogenous social effects (i.e the average peer characteristics of a CKW). I present the main result of the total monthly performance of CKWs in table 5.1. Although the observed attributes of individual CKWs (i.e., own characteristics) match exactly the average characteristics of peers (i.e., exogenous), the model is estimated with significant results.

Table 5.1 shows that regarding own characteristics, total monthly performance of CKWs increases with the age of a CKW. One possible explanation for this result is that older folks tend to rely more on the job of being a CKW, with fewer other options to focus their attention to. Thus, the sign and magnitude of the age variable seem plausible in this context. Moreover, table 5.1 shows that the total monthly performance of a CKW increases with being married. CKWs that are married have higher total monthly performance compared to their unmarried colleagues. Therefore, marital status in terms of being married, plays a vital role in individual CKW performance in the setting. The coefficient for whether a CKW is married is significant with a very high magnitude (0.93) indicating that marital status plays a critical role in the life of individual CKWs, in terms of giving them the wherewithal to focus on the CKW-job. One possible explanation for this results is that, being married frees some time for a CKW to allocate more time to working as being as a community extension agent while the spouse stays behind to work perform other vital services such as coordinating work on family plots and to also take care of domestic issues like child care. In the rural areas of Uganda including the research setting, more than 60% of families are involved in farming. Therefore, since CKWs are naturally selected from the farming population in their communities, there is high probability that every CKW is involved in either personal or family farming. As such, it is plausible to assume that being married gives a CKW an edge in community extension work compared to their cohorts that are unmarried. Hence the sign and magnitude of the marital status variable seems credible in this context.

Table 5.1 also shows that the total monthly performance of CKWs is positively correlated with the ownership of a bicycle as a means of transportation. This variable is significant

Table 5.1: Total monthly performance estimates of CKWs

	Total monthly performance	Std error
Own characteristics =$\boldsymbol{(I\text{-}G)X}$		
Age of CKW	0.0527***	0.0124
No. of CKW Training	0.0130	0.0901
CKW is married	0.929***	0.269
CKW is household head	0.170	0.292
No. of children	-0.409**	0.122
Works in hilly terrain	-0.444	0.248
Member of a farmers' group	-0.121	0.249
Has a bicycle	0.528*	0.248
Debt owed in USD	-0.000837*	0.000340
At least high school grad	0.621	0.381
Clinic in Parish	-0.0803	0.259
No breakdown of equipment	0.221	0.245
Exogenous Social effects =$\boldsymbol{(I\text{-}G)GX}$		
Age of CKW	0.0427	0.0282
No. of CKW Training	0.0114	0.193
CKW is married	-0.137	0.606
CKW is household head	2.115**	0.684
No. of children	-0.206	0.290
Works in hilly terrain	0.334	0.579
Member of a farmers' group	-1.300*	0.510
Has a bicycle	-1.664**	0.586
Debt owed in USD	-0.00157*	0.000684
At least high school grad	2.980***	0.867
Clinic in Parish	-0.485	0.603
No breakdown of equipment	-0.890	0.521
Endogenous social effects = $\boldsymbol{(I\text{-}G)Gy}$		
`Endogenous effect`	0.95***	0.2054
Number of observations	8450	8450

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

at the 10% level with a magnitude of 0.528. Bicycle constitutes a vital means of transportation for individuals in the setting. Owning a bicycle determines how fast a CKW can work across his/her operational areas. One plausible explanation for this result is that, a CKW that owns a bicycle would naturally have a quicker access to community members whether at their farms or at their homes, and thus makes it quicker for him/her to respond to their requests for agricultural information. Thus, the sign and magnitude of the bicycle ownership variable seems credible.

Moreover, table 5.1 shows that CKW performance decreases with the level of indebtedness and the number of children they have. A possible explanation for this result is that, since children (especially kids and toddlers) often need more attention, the number of children a CKW has would limit the total time available to allocate to the work of community extension. Similarly, being in debt might negatively a CKW's state of mind (in terms of being at peace and being able to concentrate on productive work). In Uganda, the CKW program consists of credit schemes to CKWs as part of the package offered by Grameen. For example, the ready-set that provides energy to charge the CKW operational cellphones is usually given as a loan to these CKWs. They are expected to pay for the ready-set over time from extra income received by charging cellphones for community members using these ready-sets[1]. However, relying on the ready-sets for extra income presents one main constraint for CKWs: -The ready-sets convert solar energy into electrical power. However, in the tropics as is with the research setting, the rainy seasons often include heavy cloud cover and rainfall, which limits sunlight for the ready-set and thus make it hard to get adequate charge to power other cellphones besides the CKW's operational cellphone[2]. Secondly, the bicycles that are given to CKWs is also a credit which they must repay. Thus, it is not surprising why the average amount of debts owned by CKWs is higher than their average

[1]In most rural communities of Uganda, consisting of the research setting, electrical power is not available. Although most community members may have cellphones, lack of power to recharge the batteries is usually a major challenge, which CKWs address through the ready-sets

[2]The android handsets used by CKWs are very poor on retaining charge. They often require an average of 2 charges per day due to the data demands through the searches

income as shown in the descriptive statistics. These high amounts of debt might negatively affect the total monthly performance of CKWs in this context. For instance, one implication of high indebtedness could mean that those with high amounts of debts may look for other jobs such as teaching and participation in community labor gangs in order to streams augment their monthly income. However, such activities may hinder a CKW's effectiveness as a community knowledge worker by affecting the total time available for community extension service. Hence the value and sign of the estimate for debt seems plausible in this context.

Some of the other variables such as the number of trainings attended, attainment of high school education, whether the equipment did not breakdown, whether CKWS works across a hilly terrain, belonging to a farmers' group, and being a household head, are not significant in this context. In particular, the result indicates that the number of trainings attended by a CKWs does not contribute to an increase in the technical ability of the CKW. This result also suggests that training programs for CKWs should be better designed to incorporate salient issues that affect the technical ability of community knowledge workers. For example, the descriptive statistics shows that CKWs had an average of 5 trainings over the period under consideration. However, certain flaws may exist with the CKW trainings programs which may hinder optimality in CKW performance. For example, the length (i.e., duration) of these trainings are usually 4 days per section and mainly involve an understanding of how to use smartphones (see section 3.2.1 above). However, other salient areas of agricultural training such as basic agronomic principles, and basic book keeping should which might add value to a CKW's technical knowledge in working with community members, are lacking in those training packages. CKWs are mainly programed to search the smartphone for information. But community members may need more information (such as in an emergencies) than just what is in the smartphone, which the CKW may not be able to provide.

The exogenous social effects are also significant for a number of variables. In particular, the result shows that the total monthly performance of a CKW increases if the average number of his peers are household heads, and if the average number of them have at least high school level of education (this might be an indication of their ability to easily understand and navigate the CKW cellphone and equipment as well as to clearly communicate in English by understanding the information in the agricultural database of the cellphone). One possible explanation for these two results is that, for one, if the average number of a CKW's peers are households heads, chances are, they are of similar age bracket with the particular CKW in question (the own characteristics shows that performance increases with age). Thus the propensity for peer interactions would be higher. Moreover, if the average number of a CKW's peers have at least high school level of education, they would do fewer invalid searches, which determines the actual total number of performance. Through their mutual interaction, the CKW would most likely also make fewer invalid searches, and he would have higher monthly performance. Thus, this estimate seems plausible in this context.

Table 5.1 also shows that if the average number a CKW's peers are members of a farmers' group, his total monthly performance decreases. One explanation for this result is that farmer's group membership places a higher demand on a CKW's time for his group members who are also his clients for agricultural information. This might leave little time for the CKW to interact effectively with other CKWs in another parish or district. Thus, if the average number of a CKW's peers belong to farmers' groups, they might have little time for him in terms of how much help he could get from them with regards to the extension work.

Moreover, table 5.1 shows that the total monthly performance of a CKW decreases with the average amount of debt owed by his peer. This sounds intuitive because indebtedness can be overwhelming (as explained under the own characteristics option). CKW's with high amount of debt might tend to do more community extension work in order to earn beyond their usual pay so that their income, less debt repayment, might be sufficient for living expenses. Thus, they would have less time to interact with their peers. This may explain the reason for the negative effect.

Similarly, table 5.1 shows that the total monthly performance of a CKW decreases if the average number of his peers have bicycles. This is counter-intuitive as one would expect that the ability of CKWs to interact with one another would increase if they have a means of transportation such as bicycle because it makes mobility easier and quicker, and thus increase the probability of meeting with one other in the same district or in nearby parishes across neighboring districts. However, if the bicycle was acquired as loan from Grameen, then this results could mean that as with indebtedness, having a bicycle might cause individual CKWs to devote greater time towards performing extension services in communities so they can earn enough to repay the loan. They might have little time for frequent interactions with other CKWs. On the flip side, even if a bicycle was not acquired on credit, having transportation facility in general, might increase the outreach capacity of a CKW, and thus cause him to desire travel to more places within their respective parishes and thus provide more agricultural information to farmers. That might take time away from mutual interactions with other CKWs.

Other explanatory variables such as average age of peers, average number of training sessions attended by peers, average number of children of peers, average number of peers working across hilly terrains, and average number of peers whose equipment never broke down, do not affect the total monthly performance of CKWs in this setting as shown by the value other coefficients which are not significant.

In terms of peer effects, table 5.1 shows that the endogenous social effect variable (i.e., proxy for peer effects) is positive and significant at the 1% level. In particular, the result indicates that a one point increase in the mean performance of the peers of a CKW induces him to increase his own monthly performance by 0.952 units. As observed in Mas and Moretti (2009), my result implies that through the effects of peers on the total monthly performance of individual CKWs, it is possible for Grameen foundation to attain a high level of monthly performance for all CKWs in the program areas by more than 50% (i.e., by about 70% increment) if they have the right mix of highly performing CKWs working as peers (or neighbors) of other CKWs that have relatively low monthly performance. Thus, my result indicates that neighbors matter in achieving higher performance among extension workers.

5.2 Diagnostics tests

In this section, I perform various diagnostics test to validate the strength and reliability of the peer effects in the total monthly performance of CKWs in Uganda. The key tests conducted include test of validity of the instruments used for identification through the generalized two-stage least squares regression, multicollinearity, and omitted variable bias test. I present results of these test as follows;

5.2.1 Estimate of endogenous social effect with district fixed effects

The high value of the endogenous social effect in the main result (table 5.1) makes me think of using district fixed effects in the computation of the endogenous social effects, since the first estimate using G2SLS assumes a random effect in the computation of the peer effect. However, with the use of district fixed effects, the value of the estimate drops to 0.712, and significant at 5% level. The result is reported in table 5.2. Table 5.2 shows that the endogenous effect, though still positive and significant, has reduced in its sign and magnitude from 0.95 to 0.72. The level of significance also reduces from 1% to 5%. This suggests that the use of district fixed effects absorbs any omitted variable bias that may have been associated with the data.

Table 5.2: Total monthly performance estimates of CKWs

	Total monthly performance	Std error
Own characteristics =***(I-G)X***		
Age of CKW	0.0527***	0.0124
No. of CKW Training	0.0130	0.0901
CKW is married	0.929***	0.269
CKW is household head	0.170	0.292
No. of children	-0.409**	0.122
Works in hilly terrain	-0.444	0.248
Member of a farmers' group	-0.121	0.249
Has a bicycle	0.528*	0.248
Debt owed in USD	-0.000837*	0.000340
At least high school grad	0.621	0.381
Clinic in Parish	-0.0803	0.259
No breakdown of equipment	0.221	0.245
Exogenous Social effects =***(I-G)GX***		
Age of CKW	0.0427	0.0282
No. of CKW Training	0.0114	0.193
CKW is married	-0.137	0.606
CKW is household head	2.115**	0.684
No. of children	-0.206	0.290
Works in hilly terrain	0.334	0.579
Member of a farmers' group	-1.300*	0.510
Has a bicycle	-1.664**	0.586
Debt owed in USD	-0.00157*	0.000684
At least high school grad	2.980***	0.867
Clinic in Parish	-0.485	0.603
No breakdown of equipment	-0.890	0.521
Endogenous social effects = ***(I-G)Gy***		
`Endogenous effect`	0.712**	0.246
Number of observations	8450	8450

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2.2 Identification test of instrument variables (IV)

In the estimation of peer effects of CKW performance in rural Uganda, the values of the test statistics associated with the generalized two-stage least squares are very important. The main test of identification: - the Hansen J Statistics, which is a test of over-identification, has a value of 25.336, with a P-val of 0.0026. Thus, I fail to reject the null hypothesis that the instrument variables used in the specification are valid instruments. This implies that the instrument variables are uncorrelated with the stochastic term, and moreover, that the excluded instruments are excluded correctly.

Moreover, other critical statistics such as the Kleibergen-Paap Wald F statistic and the Anderson canon correlation Lagrange Multiplier statistic are 5.676 and 175.472 respectively with a P-value of 0.0000 while the Cragg-Donald Wald F statistic is 16.612 and is associated with a 5% - 10% relative bias according to the Stock-Yogo critical values. These test-statistics confirm that the validity and relevance of the instruments variables and suggest that the result for the estimated value of peer effects is plausible.

5.2.3 Tests for multicollinearity

There is the possibility that including a CKW's own characteristics and the characteristics of his peers in the same regression might result to multicollinearity due simultaneity in the outcomes of CKWs as they interact with one another. This simultaneity is what Manski (1993) refers to as the *reflection* problem because it tends to cause a perfect collinearity between the expected average performance of a CKW-peer group and its average characteristics (Bramoullé, Djebbari, and Fortin, 2009). In order to address this issue, I check for multicollinearity in CKW performance by computing the variance inflation factor (VIF) for all specifications. None of the variables in all the models has a VIF equal to, or greater than 10. This indicates that multicollinearity is not a problem in the setting.

5.2.4 Test for omitted variable bias

Omitted variable bias might constitute a major challenge in the identification of peers effects of CKW performance in rural Uganda. One might wonder if the variables used in the specifications for peer effects are adequate to determine the effects of peers on total monthly performance of individual CKWs. In order to address this possible challenge, I use the Ramsey test for omitted variable bias using powers of the fitted values of the dependent variable (i.e., total monthly performance). This gives an F statistics of 1.01 with a p-value of 0.3858. It indicates that omitted variable bias is not a major problem in the original specification.

5.2.5 First-stage regression estimate of the endogenous social effects

Table 5.3 reports the first stage predicted peer effects of performance, which comprise of the endogenous social effect. The result of this regression shows that many of the instruments and excluded instruments are significant. Thus, it indicates that the first staged regression accurately predicts the peer effects of CKW performance.

5.3 Robustness checks

In this section, I check for the validity of the peer effects estimate using specifications under different conditions such as the period before and after incentive realignment in June 2011, and a change in peer group definition and composition based on the standard k-nearest neighbor weights matrix.

Table 5.3: G2SLS First-stage estimate of endogenous social effects

	Endogenous effect: Coefficient	Endogenous effect: Std error
Own characteristics		
Age of CKW	0.0065	0.0071
No. of CKW Training	-0.0439	0.0509
CKW is married	-0.2174783	0.1500
CKW is household head	0.4552***	0.1572
No. of children	-0.1338	0.0688
Works in hilly terrain	0.4110***	0.1367
Member of a farmers' group	-0.23245	0.1359
Has a bicycle	-0.0991	0.1359
Debt owed in USD	-0.0004	0.0002
No breakdown of equipment	-0.0552	0.1331
Excluded instruments		
Age of CKW	0.0849***	0.015
No. of CKW Training	-0.2196**	0.103
CKW is married	0.4702	0.324
CKW is household head	0.627	0.392
No. of children	-0.504***	0.158
Works in hilly terrain	0.002	0.315
Member of a farmers' group	-0.202	0.273
Has a bicycle	-0.826***	0.327
Debt owed in USD	-0.001**	0.0004
No breakdown of equipment	0.352	0.289
Number of observations	8450	8450

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3.1 Comparison of total monthly performance for the periods before and after incentive adjustment

In order to determine whether peer effects are uniform across the two periods before and after the realignment of performance incentive, I compare the estimates of total monthly performance of CKWs for the period before incentive realignment, and the period after incentive realignment. The period before incentive realignment comprise of six month (including December 2010 through May 2011). On the other hand, the period after incentive realignment comprise of 7 months from June 2011 to December 2011. Table 5.4 reports the estimates of the two specifications.

Table 5.4 shows that the endogenous social effect is positive and significant at the 10% level for the specification corresponding to the period prior to incentive realignment, but insignificant for the estimate corresponding to the period after incentive adjustment. The results suggests that the power of incentives (i.e., the incentive effect) smooths out the peer effects in the second specification. One possible explanation for this result is that the introduction of the higher incentive rate (or realignment) breads some amount of competitiveness into the behavior of CKWs.

The principle of games in microeconomics wherein individuals try to maximize the payoff from performance, subject to either an incentive compatibility constraint or a participant constraint, might be useful for explaining the loss of peer effects in the performance of CKWs in Uganda. The result could mean that prior to the incentive realignment (or adjustment), individual CKWs cooperate more with one another. It is possible that in the first period, some CKWs might just do enough to get by, or tend to practice copycatting by setting their performance limits in line with their peers. However, after the introduction of the incentive, individual CKWs might have taken the extension work more seriously in order to maximize their remuneration from the job by achieving an "A" grade on a monthly basis. This lat-

Table 5.4: Estimates of total monthly performance (before and after)

	Performance Before (Coefficient)	Performance Before (Std Error)	Performance After (Coefficient)	Performance After (Std Error)
Endogenous social effects				
Endogenous effect	0.9006***	0.2298	0.36119	0.2676
Own characteristics				
Age of CKW	0.0754***	0.0201	0.0333*	0.0132
No. of CKW Training	-0.286	0.146	0.269**	0.0958
CKW is married	1.005*	0.433	0.864**	0.287
CKW is household head	0.473	0.470	-0.0887	0.308
No. of children	-0.525**	0.199	-0.309*	0.127
Works in hilly terrain	-0.372	0.402	-0.506	0.260
Member of a farmers' group	-0.643	0.404	0.326	0.260
Has a bicycle	0.886*	0.402	0.222	0.258
At least high school grad	0.548	0.627	0.683	0.395
Clinic in Parish	-0.275	0.423	0.0868	0.269
Debt owed in USD	-0.00207***	0.000480	0.000222	0.000343
No breakdown of equipment	0.499	0.397	-0.0169	0.257
Exogenous social effects				
Age of CKW	0.0577	0.0462	0.0310	0.0297
No. of CKW Training	0.111	0.315	-0.0935	0.205
CKW is married	0.529	0.991	-0.309	0.603
CKW is household head	2.151*	1.091	2.186**	0.710
No. of children	0.142	0.473	-0.382	0.298
Works in hilly terrain	2.303*	0.946	-1.218*	0.595
Member of a farmers' group	-1.188	0.810	-1.374**	0.529
Has a bicycle	-1.338	0.919	-1.966**	0.626
Debt owed in USD	-0.00198	0.00113	-0.000870	0.000689
No breakdown of equipment	-0.439	0.854	-0.928	0.532
Observations	3900	-	4550	-

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ter scenario might have introduced competition into the monthly performance of individual CKWs. This might be responsible for the insignificance of the peer effects variable in the second period.

5.3.2 Comparison of total monthly performance for different peer group definitions

In order to further test the robustness of the coefficient estimate of the effect of peers in the total monthly performance of CKWs (as given in the main specification result), I estimate the total monthly performance of CKWs under two different specifications based on the nearest-neighbor definition of peer groups: - One based on a 10 - nearest neighbor matrix (i.e., K =10) and another based on a 15-nearest neighbor matrix (i.e K =15 or simply, 15NN). I refer to these two specifications as 10NN and 15NN respectively. Varying the composition of the weights matrix (based on multiples of 5) will help to test the validity and consistency of the effects of peers on total monthly performance through the estimates of the endogenous social effect under different conditions. Table 5.5 reports the estimates of these robustness specifications.

Table 5.5 shows that the endogenous social effect across both specifications is positive and significant at the 10% level. Although the main aim of these specifications is to check for the consistency of the endogenous social effects, table 5.5 shows that there are significant estimates for some of the own characteristics and exogenous social effects variables as well. This robustness result indicates that the estimated social effect (i.e peer effects) in the performance of individual CKWs is consistent and reliable based on the original specification of 5-nearest neighbors.

However, table 5.5 shows that the strength of the peer effects under these larger peer group definitions (or peer interaction matrices) is relatively weak (at 10%) compared to

Table 5.5: Estimates of total monthly performance based on 10NNs and 15NNs

	Performance 10NN Coefficient	Performance 10NN Std Error	Performance 15NN Coefficient	Performance 15NN Std Error
Endogenous social effects				
Endogenous effect	0.962*	0.387	0.811*	0.388
Own characteristics				
Age of CKW	0.0527***	0.0124	0.0524***	0.0124
No. of CKW Training	0.0130	0.0901	0.0142	0.0902
CKW is married	0.929***	0.269	0.932***	0.269
CKW is household head	0.170	0.292	0.167	0.292
No. of children	-0.409***	0.122	-0.410***	0.122
Works in hilly terrain	-0.444	0.284	-0.443	0.248
Member of a farmers' group	-0.121	0.249	-0.114	0.248
Has a bicycle	0.528*	0.248	0.524*	0.247
Debt owed in USD	-0.000837*	0.000340	-0.000832*	
No breakdown of equipment	0.221	0.245	0.219	0.245
At least high school grad	0.621	0.381	0.625	0.381
Exogenous social effects				
Age of CKW	0.116*	0.0460	0.110	0.0592
No. of CKW Training	-0.186	0.284	-0.0980	0.329
CKW is married	-1.846*	0.889	-0.0980	1.224
CKW is household head	1.093	1.001	2.181	1.237
No. of children	-0.830*	0.403	0.0920	0.510
Works in hilly terrain	1.320	0.874	2.177*	0.994
Member of a farmers' group	-2.147**	0.693	-0.637	0.884
Has a bicycle	-0.569	0.890	-1.346	1.181
Debt owed in USD	-0.00106	0.00109	-0.00182	0.00149
At least high school grad	1.318	1.263	-1.142	1.567
No breakdown of equipment	0.406	0.788	0.390	0.965
Observations	8450	-	8450	-

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the the estimates of the main result which is significant at 5%. One possible explanation for the relative weakness in the significance of the endogenous social effect variable with larger numbers of neighbors is that, with more individuals participating in a social network interaction, the probability of any CKW i to interact with CKW j decreases compared to a situation with fewer members in the network. The result is consistent with the standard literature on peer effects and social network analysis. For instance, the literature suggest that a higher density of a social network interaction reduces the precision and strength of identification (See Bramoullé, Djebbari, and Fortin (2009); Wasserman and Faust (1994); Wasserman and Galaskiewicz (1994)).

Chapter 6

Conclusion

In this study, I have utilized advanced methods of social network analysis and spatial econometrics to identify peer effects in the performance of rural extension workers known as community knowledge workers (CKWs) in Uganda. The research setting consists of the operational districts of the CKW program in Uganda under the management and supervision of Grameen foundation. Recent studies such as Moffitt (2001); Cohen-Cole (2006); Bramoullé, Djebbari, and Fortin (2009); De Giorgi, Pellizzari, and Redaelli (2010); Lee (2007), and Krishnan and Patnam (2014) proffer solution to the reflection problem which limits the potential for identification of peer effects among interacting agents in a group or social network setting (Manski, 1993). In particular, these advances in social network analysis, when applied to the standard linear-in-means model which had been criticized for its implausible identification of peer effects (Manski (1993); Manski (2000)), results to identification of peer effects in a wide variety of context. This stylized or modified version of the linear-in-means model solves the identification problem by separating and disentangling the effects of social interaction among peers into endogenous and exogenous effects (Bramoullé, Djebbari, and Fortin (2009); Moffitt (2001)).

In the present analysis, I use the empirical application of Bramoullé, Djebbari, and Fortin (2009) with a relevant agricultural setting application (Krishnan and Patnam, 2014), to identify peer effects among 650 community knowledge workers (CKWs) across 13districts in Uganda over a 13-month period of operation. The period considered include December 2010 through December 2011. Using the administrative records of the monthly performance of these CKWs based on their use of smarthphone technology containing an agricultural information database for community extension services, I constitute a panel data set that comprise of information on the socioeconomic attributes (i.e., own characteristics) of individual CKWs, the characteristics of their peers or neighbors in the setting, and the geographic coordinates of their locations within their operational districts.

I utilize a generalized two-staged least square (G2SLS) method of estimation to undertake this analysis in order to identify peer effects in the performance of individual CKWs by separately estimating the endogenous social effect and the exogenous effect among these CKWs. Similar to Krishnan and Patnam (2014), I first regress the dependent variable (i.e., total monthly performance) on all the exogenous characteristics of CKWs, and then used the parameter estimates to obtain higher order spatial lags from the predicted values of those estimates. The lags of the higher order predicted values provide the required set of instrument variables (IVs) which are applied in the panel data to identify peer effects in the total monthly performance of CKWs. I use the estimate of endogenous social effect as proxy for peer effects in the total monthly performance of CKWs (see also Bramoullé, Djebbari, and Fortin (2009)). This total monthly performance is measured by the number of valid *searches* or total agricultural information provided to local farmers when a CKW navigates the agricultural database in the official CKW cellphone (CKWs use an Android smartphone). The search records are captured by Grameen through a monitoring system which transmits precise and accurate information about the search at any given point in time.

The result from the main specification shows that the estimated peer effects in the total monthly performance of a CKW in Uganda is positive (0.952), and significant at the 1% level. This result indicates that a one point increase in the average performance of a CKW's peers will induce him to increase his own performance by 0.952 units. This result is consistent with a series of robustness tests including variation in peer-interaction matrix (i.e, peer group specification) and various diagnostic tests performed in the post-estimation. In particular, the values of the test statistics and regression diagnostics including test for multicollinearity, omitted variable bias, and test of validity and relevance of the instrument variables used in the specification, suggest that the estimate of endogenous social effects is plausible.

I conclude that the significant and positive values of endogenous social effects associated with the total monthly performance of CKWs in my research setting is an indicator of positive peer effects among CKWs as regards to their total monthly performance. Hence, this research suggests that peer effects exist in the performance of agricultural extension workers in general.

Further, I argue that identification of peer effects on total monthly performance of CKWs is better within a relatively less dense medium of social interaction (i.e., peer network) than a network or peer group setting with a high density of social interaction. For example, the estimates from a specification with 5 peers (i.e., 5-nearest neighbors) is much more significant than an estimate from a specification with 15 peers.

6.1 Applicability and relevance of the result

The result from this analysis is relevant for diverse sectors including but not limited to the following:

6.1.1 Extension policy

The literature suggest that identification of peer effects among economic agents can enhance the construction of behavioral models that can reliably predict future outcomes under identical or (closely identical) conditions (Manski (1993); Manski (2000); Akerlof (1997);

Bramoullé, Djebbari, and Fortin (2009); De Giorgi, Pellizzari, and Redaelli (2010)). For instance, Sacerdote (2001) show that through peer effects, it is possible to predict certain behavioral patterns among college students. For example, the choice of association of freshmen students regarding fraternity/sorority membership. Moreover, Mas and Moretti (2009) suggest that through peer effects, it is possible to make informed decisions about worker productivity in terms of the most efficient ways of optimizing the output (or performance) of a set of workers in a retail store or supermarket chain setting. Such implication can be extended to agricultural extension workers by predicting and influencing their outcomes such as performance level, through an understanding of their associative (or interactive) relationships with experienced co-workers. That is, it is possible to redefine extension policy that maximizes extension workers' output by assigning higher performing extension staff to areas where they could influence the performance of their weaker peers through their on-the-job interaction.

The result of this study suggest that the marginal effect of attending extension training programs and workshops by CKWs is insignificant. That is, additional training does not necessarily add value in terms of technical ability. Thus, a plausible extension policy that derives from this research is that training programs for extension workers should focus less on the number of trainings delivered (or training sessions conducted in a given period), and more on the quality (in terms of component and probably duration/length) of such trainings than the number of training sessions conducted. In other words, extension staff trainings should be designed to be all-encompassing (i.e., relevant in terms of the needs of the intended target communities where the extension staff will operate). For example, trainings could be better designed to incorporate other salient factors such as community development, basic financial management principles that are usually not not part of the agricultural information package contained in the agricultural database of the cellphones. This finding is consistent with prior research on the relationships between human capital formation through improvement in the quality of training and economic development (Liu and Batt (2007); Preacher and Hayes

(2008); Schütt (2003)).

Moreover, the findings suggest that total monthly performance of CKWs is negatively correlated with the amount of debt owed by CKWs. In particular, the finding (from the descriptive statistics) shows that the average amount of debts owed by CKWs exceed their average personal incomes. The CKW program entails loans in various forms such as monthly payment/salary advances, and credit in the form of payment for the ready-set and bicycles provided to CKWs. The ready-set provide power for charging the CKW's cellphone and those of community members for a small fee which is expected to provide additional income to CKWs. However, since the ready-sets are solar energy dependent, they are usually not effective to charge large number of cellphones due poor weather conditions especially during raining seasons which limit the amount of solar energy available to power the ready-sets. Further, CKWs who receive bicycles from the program are required to make installment payments for those bicycles. Payments are often deducted from the wages. This policy of "garnishing the wages" of CKWs could lead to CKWs often having to cope with financial difficulty which may limit their concentration on the job of community extension.

In all specifications, the coefficient for the effects of debt on performance appears negative, albeit with smaller magnitude in some cases. Thus, a good extension policy should promote a reasonable means of compensation for extension workers in sub-Sahara Africa in general, and in the CKW program in particular. Although the incentive scheme for the CKW program is designed to motivate and induce higher performance, the overall total payment for the topmost performance is 60,000UGX which is approximately $24 at an exchange rate of 2500 UGX to the US dollar. Hence heavy debt burden in the form of payment for equipment, bicycle, and salary advances are not effective policies, and should be revised since it appears to limit the performance of CKWs. Therefore, this analysis suggests that credit to CKWs by the program administration should be allowed only under certain conditions that will not hinder the optimality of CKW performance. The review of such policy may also result in the sustainability of the CKW program and community development as a whole.

6.1.2 Extension management

My research findings could be relevant to the management community of extension programs and projects in various ways. The findings from this research suggest that managers of extension programs should be able to maximize the performance of extension workers by appropriately organizing work/task teams (like what obtains in corporate organizations and businesses). The sign and magnitude of the coefficient of the proxy for peer effects (i.e the endogenous social effect variable) in the main specification suggests that before the incentive adjustment in June 2011, there was very high correlation in the performance of individual CKWs in Uganda. However, the incentive realignment wipes out the peer effects when the two periods are considered separately. For example, the mean performance of the two periods, as shown by the descriptive statistics, is 8 points higher in the second period than the first. This suggests that both peer effects and incentive effects are strategic in inducing extension performance. In particular, the finding suggests that peer effects are vital for inducing higher performance for the longer term, whereas incentive effect seems to be stronger and more effective for the short term.

Therefore, in line with other findings in the literature on peer effects and worker productivity (see Mas and Moretti (2009) and Herries, Rees, and Zax (2003)), teams of extension workers that consist of high performance oriented individuals should be formed in the implementation of community extension right from the get-go. The teams should normally be a mixture of experienced extension workers who can sustain longer term momentum in the group, and initially motivate them by an rolling incentive scheme such as the system in the CKW program.

6.1.3 Industrial organization (I/O) of extension

Peer effects among extension workers like the CKWs, have the promise of improving extension if they are well managed. Thus, this study has vital implication and relevance to the industrial organization of extension. Extension is a global phenomenon that remains to be fully organized and industrialized. In many settings, especially in the developing world economies, extension remains a minute part of agriculture as a sector. However, the literature suggest that extension is critical for economic development through improved and productive agricultural systems. There is need to better organize national extension systems within an industrial organization (I/O) framework. This means, extension should be treated as a stand-alone-sector of national institutions so that it can be cross-cutting, serving diverse other sectors such agriculture, natural resources, community development, and education through non-formal education systems.

A better systematization and institutionalization of extension within and I/O framework can be a means to cost minimization in extension programs such as those as vital as staff trainings, recruitment, monitoring and evaluation of programs, as well as development research. Through proper mixing of extension workers at the field level, social interaction among them (especially in partially overlapping settings like those in the CKWs setting who interact mainly through cellphones), there would be a high tendency for these extension agents to influence the level of performance of their peers. Thus, even average performers may produce at a higher production possibility frontier. However, there has to be a way of identifying higher performers from low performers. An I/O dimension to extension can lend itself to the establishment of institutional guides that can help in deciphering the composition of the performance of extension workers.

Therefore, it would be expedient for private institutions such as Grameen foundation to increase their participation in extension delivery through various models including a robust staff allocation system that forms teams of small groups from where social network can ignite peer effects, which can further improve performance of the team.

6.1.4 Future research

This study provides a baseline for further research into the performance of extension which could provide a good proxy for the productivity of extension systems. This analysis has attempted to break (or open) the black box prism through which extension programs have often been analyzed without regard to its internal workings (i.e., separate components). I contribute to filling this gap by showing through peer effects, that a lot more can be learned about extension performance. For instance, although trainings comprise the main explanatory variable for determining the performance of extension workers in the current study, there is no evidence of the direct role that additional trainings play on the performance of CKWs in this setting. Moreover, lack of direct information on the quality of the trainings received by CKWs and its implication on the performance of extension systems might be a good area for further research.

Another possible area of research emanating from this analysis is a side-by-side comparison of peer effects and the effects of incentives in terms of how they both influence higher performance of extension workers in divers settings. The finding also suggests that incentive effects are stronger than peers effects for inducing higher performance of extension workers in a short term. However, this finding remains to be tested and validated in a strict comparison of the two effects (that was not the target of this analysis).

Finally, a future research area relates to the timing of submission of the searches. The kernel density plots (figures 4.1 and 4.2) and the Moran's scatterplots (figures 4.3-4.9) suggest that a lot might be going on in the CKW program. One might want to investigate if the performance of extension workers is more likely to be time-specific or seasonally determined. For example, a regression discontinuity approach might be a good future area to explore on the monthly performance of extension staff in this context and elsewhere.

6.2 Limitations of the study

As with many empirical analyses, this study has certain limitations.

6.2.1 Single performance matrix

For one, this study uses a single measure of performance (i.e., total number search per month) for the productivity of community knowledge workers in Uganda. There could be many other measures of extension workers' performance, such as the quality of time spent advising farmers during each query (i.e., search) period, the effectiveness of the information delivered to specific farmers (for example, agronomic information might be given in an ambiguous manner, which a typical smallholder farmer may not properly understand and thus, might not effectively apply such agricultural information). However, data limitations prevent a complete assessment of the various possible measures of CKW performance in the present analysis.

6.2.2 Use of training as an index of performance

Secondly, the use of training as proxy for ability and estimating its indirect effect on the the total monthly CKW performance, which is the dependent variable, might also limit the precision of the outcome because CKW training programs (even if they prove effective at a one time or the other) may not be all inclusive to adequately equip these CKWs for actual extension services. In other words, no "crash course" can replace a full-fledged extension education which takes time to accomplish. This constitutes a big challenge in the present setting because the extension trainings received by CKWs are rather short, and thus, limited in scope. For instance, De Grip and Sauermann (2013) note that;

> It is important to have appropriate outcomes to measure the returns to training. When the researcher is interested in measuring the effectiveness or the transfer of training, the most appropriate measure is a measure that captures a workers productivity, since it allows to measure the value added of what is transferred from training to the actual task of the worker. In reality, however, it is difficult to find measures of productivity that are measurable and comparable across workers or firms (p.30).

As it turns out, the coefficient estimate for training is not significant in the main specification and those for the robustness tests. However, the average performance from all various descriptive statistics of the data are fairly high (at least 40 searches) across the various specifications. This might be a signal that the number of training sessions attended by CKWs may not be the best proxy for a CKW's ability to deliver community extension services in Uganda.

References

Aker, J., and I. Mbiti (2010): "Mobile phones and economic development in Africa," *Center for Global Development Working Paper*.

Aker, J. C. (2010): "Information from markets near and far: Mobile phones and agricultural markets in Niger," *American Economic Journal: Applied Economics*, 2(3), 46–59.

Aker, J. C. (2011): "Dial A for agriculture: A review of information and communication technologies for agricultural extension in developing countries," Working Paper 269, Center for Global Development.

Akerlof, G. A. (1997): "Social distance and social decisions," *Econometrica*, 65(5), 1005–1028.

Anderson, J. R., and G. Feder (2003): "Rural extension services," Policy Research Working Paper Series 2976, The World Bank.

Anderson, J. R., and G. Feder (2004): "Agricultural extension: Good intentions and hard realities," *The World Bank Research Observer*, 19(1), 41–60.

Anselin, L. (1988): "Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity," *Geographical Analysis*, 20(1), 1–17.

——— (1990): "Some robust approaches to testing and estimation in spatial econometrics," *Regional Science and Urban Economics*, 20(2), 141–163.

——— (2002): "Under the hood: Issues in the specification and interpretation of spatial regression models," *Agricultural Economics*, 27(3), 247–267.

——— (2010): "Thirty years of spatial econometrics," *Papers in Regional Science*, 89(1), 3–25.

Anselin, L., A. K. Bera, R. Florax, and M. J. Yoon (1996): "Simple diagnostic tests for spatial dependence," *Regional Science and Urban Economics*, 26(1), 77–104.

Axinn, G. H., and S. Thorat (1972): *Modernizing world agriculture: A comparative study of agricultural extension education systems*. Praeger New York.

Baltagi, B., and L. Liu (2011): "Instrumental variable estimation of a spatial autoregressive panel model with random effects," *Economics Letters*, 111, 135137.

Bandiera, O., and I. Rasul (2006): "Social networks and technology adoption in Northern Mozambique," *Economic Journal*, 116(514), 869–902.

Banerjee, A. V. (1992): "A simple model of herd behavior," *The Quarterly Journal of Economics*, 107(3), 797–817.

Belay, K., and D. Abebaw (2004,): "Challenges facing agricultural extension agents: A case study from South-Western Ethiopia," *African Development Review*, 16(1), 139–168.

Bell, K. P., and T. J. Dalton (2006): "Spatial economic analysis in data-rich environments," 2006 Annual Meeting, August 12-18, 2006, Queensland, Australia 25241, International Association of Agricultural Economists.

Bernasco, W., T. de Graaff, J. Rouwendal, and W. Steenbeek (2012): "Social interactions and crime revisited: An investigation using individual offender data in Dutch neighborhoods," Discussion Paper 12-108, Tinbergen Institute.

Bernheim, B. D. (1994): "A theory of conformity," *Journal of Political Economy*, 102(5), 841–77.

Bertrand, M., E. F. P. Luttmer, and S. Mullainathan (2000): "Network effects and welfare cultures," *The Quarterly Journal of Economics*, 115(3), 1019–1055.

Betz, M. R. (2009): "Effectiveness of agricultural extension with respect to farm size: The case of Uganda," Annual Meeting Paper, July 26-28, 2009, Milwaukee, Wisconsin 49471, Agricultural and Applied Economics Association.

Beugnot, J., B. Fortin, G. Lacroix, and M. C. Villeval (2013): "Social networks and peer effects at work," IZA Discussion Papers 7521, Institute for the Study of Labor.

Bikhchandani, S., D. Hirshleifer, and I. Welch (1992): "A theory of fads, fashion, custom, and cultural change as informational cascades," *Journal of Political Economy*, pp. 992–1026.

——— (1998): "Learning from the behavior of others: Conformity, fads, and informational cascades," *The Journal of Economic Perspectives*, 12(3), 151–170.

Bindlish, V., and R. E. Evenson (1997): "The impact of T&V extension in Africa: The experience of Kenya and Burkina Faso," *The World Bank Research Observer*, 12(2), pp. 183–201.

Birkhaeuser, D., R. E. Evenson, and G. Feder (1991): "The economic impact of agricultural extension: A review," *Economic Development and Cultural Change*, 39(3), pp. 607–650.

Bramoullé, Y., H. Djebbari, and B. Fortin (2009): "Identification of peer effects through social networks," *Journal of Econometrics*, 150(1), 41–55.

Bursztyn, L., F. Ederer, B. Ferman, and N. Yuchtman (2012): "Understanding peer effects in financial decisions: Evidence from a field experiment," NBER Working Papers 18241, National Bureau of Economic Research, Inc.

Calv-Armengol, A., E. Patacchini, and Y. Zenou (2005): "Peer effects and social networks in education and crime," Working Paper Series 645, Research Institute of Industrial Economics.

Camacho, A., and E. Conover (2011): "The impact of receiving price and climate information in the agricultural sector," Discussion paper, IDB Working Paper Series.

Card, D., and L. Giuliano (2013): "Peer effects and multiple equilibria in the risky behavior of friends," *The Review of Economics and Statistics*, 95(4), 1130–1149.

Case, A. C. (1991): "Spatial patterns in household demand," *Econometrica*, 59(4), 953–65.

Chew, H. E., V. P. Ilavarasan, and M. R. Levy (2013): "Mattering matters: Agency, empowerment, and mobile phone use by female microentrepreneurs," *Information Technology for Development*, pp. 1–17.

Christiaensen, L., L. Demery, and J. Kuhl (2011): "The (evolving) role of agriculture in poverty reduction–An empirical perspective," *Journal of Development Economics*, 96(2), 239–254.

Cipollone, P., and A. Rosolia (2007): "Social interactions in high school: Lessons from an earthquake," *American Economic Review*, 97(3), 948–965.

Cliff, A. D., and J. K. Ord (1981): *Spatial processes: Models & applications*, vol. 44. Pion London.

Cohen-Cole, E. (2006): "Multiple groups identification in the linear-in-means model," *Economics Letters*, 92(2), 157–162.

Conley, T. G., and C. R. Udry (2010): "Learning about a new technology: Pineapple in Ghana," *American Economic Review*, 100(1), 35–69.

Cont, R., and J.-P. Bouchaud (2000): "Herd behavior and aggregate fluctuations in financial markets," *Macroeconomic Dynamics*, 4(2), 170–196.

Craig, B. J., P. G. Pardey, and J. Roseboom (1997): "International productivity patterns: Accounting for input quality, infrastructure, and research," *American Journal of Agricultural Economics*, 79(4), 1064–1076.

Davis, K. (2008): "Extension in sub-Saharan Africa: Overview and assessment of past and current models and future prospects," *Journal of International Agricultural and Extension Education*, 15(3), 15–28.

De Giorgi, G., M. Pellizzari, and S. Redaelli (2010): "Identification of social interactions through partially overlapping peer groups," *American Economic Journal: Applied Economics*, 2(2), 241–75.

De Grip, A., and J. Sauermann (2013): "The effect of training on productivity: The transfer of on-the-job training from the perspective of economics," *Educational Research Review*, 8, 28–36.

Dethier, J.-J., and A. Effenberger (2012): "Agriculture and development: A brief review of the literature," *Economic Systems*, 36(2), 175–205.

Diao, X., P. B. Hazell, D. Resnick, and J. Thurlow (2007): *The role of agriculture in development: Implications for Sub-Saharan Africa*, vol. 153. Intl Food Policy Res Inst.

Dinar, A. (1996): "Extension commercialization: How much to charge for extension services," *American Journal of Agricultural Economics*, 78(1), 1–12.

Donner, J. (2008): "Research approaches to mobile use in the developing world: A review of the literature," *The Information Society*, 24(3), 140–159.

——— (2009): "Blurring livelihoods and lives: The social uses of mobile phones and socioeconomic development," *Innovations*, 4(1), 91–101.

Duflo, E., and E. Saez (2003): "The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment," *The Quarterly Journal of Economics*, 118(3), 815–842.

Durlauf, S. N., and Y. M. Ioannides (2010): "Social interactions," *Annu. Rev. Econ.*, 2(1), 451–478.

Eidman, V. R. (1986): "Restructuring agricultural economics extension to meet changing needs: Discussion," *American Journal of Agricultural Economics*, 68(5), 1310–1312.

Evenson, R. E. (1988): "Agricultural household models: Extension, application and policy," *Journal of Development Economics*, 28(1), 147–151.

Feder, G., L. J. Lau, and R. H. Slade (1987): "Does agricultural extension pay? The training and visit system in North-Western India," *American Journal of Agricultural Economics*, 69(3), pp. 677–686.

Feder, G., and R. Slade (1985): "The role of public policy in the diffusion of improved agricultural technology," *American Journal of Agricultural Economics*, 67(2), 423–428.

Feder, G., and D. L. Umali (1993): "The adoption of agricultural innovations: A review," *Technological Forecasting and Social Change*, 43(3), 215–239.

Fei, J. C. H., and G. Ranis (1961): "Unlimited supply of labour and the concept of balanced growth," *The Pakistan Development Review*, 1(3), 29–58.

Fischer, M. M. (1996): *Spatial analytical*, vol. 4. CRC Press.

Fortin, B., and M. Yazbeck (2011): "Peer effects, fast-food consumption and adolescent weight gain," *Cirano-scientific Publications 2011s-20*.

Foster, A. D., and M. R. Rosenzweig (1995): "Learning by doing and learning from others: Human capital and technical change in agriculture," *Journal of Political Economy*, pp. 1176–1209.

Futch, M. D., and C. T. McIntosh (2009): "Tracking the introduction of the village phone product in Rwanda," *Information Technologies & International Development*, 5(3).

Garrett, T. A. (2001): "Economies of scale and inefficiency in county extension councils: A case for consolidation?," *American Journal of Agricultural Economics*, 83(4), 811–825.

Gautam, M., and J. R. Anderson (1999): *Reconsidering the evidence on returns to T&V extension in Kenya*, vol. 2098. World Bank Publications.

Glaeser, E., J. Scheinkman, and J. Sacerdote (1995): "Crime and social interactions," Working Papers e-95-2, Hoover Institution, Stanford University.

Godfray, H. C. J., J. R. Beddington, I. R. Crute, L. Haddad, D. Lawrence, J. F. Muir, J. Pretty, S. Robinson, S. M. Thomas, and C. Toulmin (2010): "Food security: The challenge of feeding 9 billion people," *Science*, 327(5967), 812–818.

Gollin, D., S. Parente, and R. Rogerson (2002): "The role of agriculture in development," *American Economic Review*, 92(2), 160–164.

Gravelle, H., R. Santos, and L. Siciliani (2013): "Does a hospitals quality depend on the quality of other hospitals? A spatial econometrics approach to investigating hospital quality competition," Working Papers 082cherp, Centre for Health Economics, University of York.

Gruber, H., and P. Koutroumpis (2011): "Mobile telecommunications and the impact on economic development," *Economic Policy*, 26(67), 387–426.

Haggblade, S. (2007): "Returns to Investment in Agriculture," Food Security Collaborative Policy Briefs 54625, Michigan State University, Department of Agricultural, Food, and Resource Economics.

Hanushek, E. A., J. F. Kain, J. M. Markman, and S. G. Rivkin (2001): "Does peer ability affect student achievement?," NBER Working Papers 8502, National Bureau of Economic Research, Inc.

Herries, J., D. I. Rees, and J. S. Zax (2003): "Interdependence in worker productivity," *Journal of Applied Econometrics*, 18(5), 585–604.

Hess, P. N. (2013): *Economic growth and sustainable development*. Routledge.

Holland, J. L. (1996): "Exploring careers with a typology: What we have learned and some new directions.," *American Psychologist*, 51(4), 397.

Hunt, R. C. (2000): "Labor productivity and agricultural development: Boserup revisited," *Human Ecology*, 28(2), pp. 251–277.

Ilavarasan, P. V., and M. R. Levy (2012): "ICT access and use by microentrepreneurs in Mumbai, India: A value chain model analysis," in *Proceedings of the Fifth International Conference on Information and Communication Technologies and Development*, pp. 259–267. ACM.

Ioannides, Y. M., and J. E. Zabel (2008): "Interactions, neighborhood selection and housing demand," *Journal of Urban Economics*, 63(1), 229–252.

Jackson, M. O. (2005): "The economics of social networks," Working Paper 1237, California Institute of Technology, Division of the Humanities and Social Sciences.

Jain, T., and M. Kapoor (2013): "The impact of study groups and roommates on academic performance," *Working Paper, Indian School of Business*, No. ISB-WP/103/2012.(10.2139/ssrn.2147225).

Jensen, R. (2007): "The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector," *The Quarterly Journal of Economics*, 122(3), 879–924.

Kelejian, H. H., and I. R. Prucha (1998): "A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances," *The Journal of Real Estate Finance and Economics*, 17(1), 99–121.

Knight, T. O., S. R. Johnson, and R. M. Finley (1987): "Extension program evaluation using normative decision models," *American Journal of Agricultural Economics*, 69(2), pp. 338–348.

Knutson, R. D. (1986): "Restructuring agricultural economics extension to meet changing needs," *American Journal of Agricultural Economics*, 68(5), 1297–1306.

Kostov, P., and J. Lingard (2005): "Disentangling the social and economic dimensions of agricultural behaviour: What role for institutions and social capital?," 94th Seminar, April 9-10, 2005, Ashford, UK 24436, European Association of Agricultural Economists.

Krishnan, P., and M. Patnam (2014): "Neighbors and extension agents in Ethiopia: Who matters more for technology adoption?," *American Journal of Agricultural Economics*, 96(1), 308 – 327.

Lee, L.-f. (2007): "Identification and estimation of econometric models with group interactions, contextual factors and fixed effects," *Journal of Econometrics*, 140(2), 333–374.

Lewis, W. A. (1954): "Economic development with unlimited supplies of labour," *The Manchester School, Blackwell Publishing Ltd,*, 22, 139–191.

LIPTON, M., AND R. LONGHURST (1989): *New seeds and poor people.* Johns Hopkins University Press Baltimore.

LIU, X., AND R. BATT (2007): "Economic pay-offs to informal training: Evidence from routine service work, the," *Indus. & Lab. Rel. Rev.*, 61, 75.

LIVERPOOL-TASIE, L. S. O., AND A. WINTER-NELSON (2012): "Social learning and farm technology in Ethiopia: Impacts by technology, network type, and poverty status," *Journal of Development Studies*, 48(10), 1505–1521.

LOUREIRO, P. R., M. J. C. D. MENDONA, T. B. S. MOREIRA, AND A. SACHSIDA (2009): "Crime, economic conditions, social interactions and family heritage," *International Review of Law and Economics*, 29(3), 202–209.

MAERTENS, A., AND C. B. BARRETT (2013): "Measuring social networks' effects on agricultural technology adoption," *American Journal of Agricultural Economics*, 95(2), 353–359.

MANSKI, C. (2000): "Economic analysis of social interactions.," *Journal of Economic Perspectives*, 14(3), 115–136.

MANSKI, C. F. (1993): "Identification of endogenous social effects: The reflection problem," *Review of Economic Studies*, 60(3), 531–42.

MARKMAN, J. M., E. A. HANUSHEK, J. F. KAIN, AND S. G. RIVKIN (2003): "Does peer ability affect student achievement?," *Journal of Applied Econometrics*, 18(5), 527–544.

MAS, A., AND E. MORETTI (2009): "Peers at work," *American Economic Review*, 99(1), 112–45.

MCCOLE, D., M. J. CULBERTSON, M. SUVEDI, AND P. E. MCNAMARA (2014): "Addressing the challenges of extension and advisory services in Uganda: The Grameen Foundations Community Knowledge Worker program," *Journal of International Agricultural and Extension Education.*, 21(1).

MCCUNN, A., AND W. E. HUFFMAN (2000): "Convergence in US productivity growth for agriculture: Implications of interstate research spillovers for funding agricultural research," *American Journal of Agricultural Economics*, 82(2), 370–388.

MITTAL, S., S. GANDHI, AND G. TRIPATHI (2010): *Socio-economic impact of mobile phones on Indian agriculture.* Indian Council for Research on International Economic Relations New Delhi.

MOFFITT, R. A. (2001): "Policy interventions, low-level equilibria, and social interactions," *Social dynamics*, 4, 45–82.

MUNSHI, K. (2003): "Networks in the modern economy: Mexican migrants in the US labor market," *The Quarterly Journal of Economics*, 118(2), 549–599.

Muto, M. (2012): "The impacts of mobile phones and personal networks on rural-to-urban migration: Evidence from Uganda," *Journal of African Economies*, 21(5), 787–807.

Muto, M., and T. Yamano (2009): "The impact of mobile phone coverage expansion on market participation: Panel data evidence from Uganda," *World Development*, 37(12), 1887–1896.

Nayyar, P. R. (1993): "Performance effects of information asymmetry and economies of scope in diversified service firms," *Academy of Management Journal*, 36(1), 28–57.

Nicholls, W. H. (1970): "The transformation of agriculture in a semi-industrialized country: The case of Brazil," in *The Role of Agriculture in Economic Development*, NBER Chapters, pp. 311–386. National Bureau of Economic Research, Inc.

Nicolson, W., and C. Snyder (2008.): *Microeconomic theory: Basic principles and extensions.* Thomson Higher Education, 5191 Natorp Boulervard Mason, OH 45040, USA, tenth edn.

Norton, G. W., J. Alwang, and W. A. Masters (2006): *The economics of agricultural development.* Routedge, London.

Patacchini, E., and Y. Zenou (2007): "Ethnicity and spatial externalities in crime," Discussion Paper 6130, Stockholm University; Research Institute of Industrial Economics (IUI); Institute for the Study of Labor (IZA); Centre for Economic Policy Research (CEPR).

Picciotto, R., and J. R. Anderson (1997): "Reconsidering agricultural extension," *World Bank Research Observer*, 12(2), 249–59.

Porter, G. (2012): "Mobile phones, livelihoods and the poor in sub-saharan africa: Review and prospect," *Geography Compass*, 6(5), 241–259.

Preacher, K. J., and A. F. Hayes (2008): "Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models," *Behavior Research Methods*, 40(3), 879–891.

Qamar, M. K. (2005): "Modernizing national agricultural extension systems. A practical guide for policy-makers of developing countries," Discussion paper, Food and Agriculture Organization of the UN.

Roe, B., T. C. Haab, and B. Sohngen (2004): "The value of agricultural economics extension programming: An application of contingent valuation," *Applied Economic Perspectives and Policy*, 26(3), 373–390.

Rostow, W. W. (1956): "The take-off into self-sustained growth," *The Economic Journal*, 66(261), 25–48.

Sacerdote, B. (2001): "Peer effects with random assignment: Results for dartmouth roommates," *The Quarterly Journal of Economics*, 116(2), 681–704.

SCHÜTT, F. (2003): *The importance of human capital for economic growth*. Inst. für Weltwirtschaft und Internationales Management.

SCOTT, J. (2013): *Social network analysis*. SAGE Publications.

STERN, D. (1982): "Economic feasibility of on-the-job training," *Economics of Education Review*, 2(2), 157 – 173.

STONEMAN, P., AND P. DIEDEREN (1994): "Technology diffusion and public policy," *The Economic Journal*, 104(425), 918–930.

SVENSSON, J., AND D. YANAGIZAWA (2009): "Getting prices right: The impact of the market information service in Uganda," *Journal of the European Economic Association*, 7(2-3), 435–445.

TAN, T. F., AND S. NETESSINE (2012): "When does the devil make work? An empirical study of the impact of workload on worker productivity," Discussion paper, Alliance Center for Global Research and Education.

THORBECKE, E. (1970): *The role of agriculture in economic development*, vol. 21 of *NBER Book Chapters*. National Bureau of Economic Research, Inc.

TOPA, G. (2001): "Social interactions, local spillovers and unemployment," *Review of Economic Studies*, 68(2), 261–95.

TROGDON, J. G., J. NONNEMAKER, AND J. PAIS (2008): "Peer effects in adolescent overweight," *Journal of Health Economics*, 27(5), 1388–1399.

UBOS (2013a): "2002 Housing Census: Analytical Report," Uganda Bureau of Statistics.

——— (2013b): "Statistical Abstract," Uganda Bureau of Statistics.

UMALI-DEININGER, D. (1997): "Public and private agricultural extension: Partners or rivals?," *World Bank Research Observer*, 12(2), 203–24.

VAN CAMPENHOUT, B. (2013): "Is there an app for that? The impact of community knowledge workers in uganda," Discussion paper, International Food Policy Research Institute (IFPRI).

VAN CAMPENHOUT, B., K. PAUW, AND N. MINOT (2013): "The impact of food prices shocks in Uganda: First-order versus long-run effects:," IFPRI discussion papers 1284, International Food Policy Research Institute (IFPRI).

WASSERMAN, S., AND K. FAUST (1994): *Social network analysis: Methods and applications*. Cambridge University Press.

WASSERMAN, S., AND J. GALASKIEWICZ (1994): *Advances in social network analysis: Research in the social and behavioral sciences*, Focus Edition. SAGE Publication.

Wooldridge, J. M. (2010a): *Econometric analysis of cross section and panel data*, no. 0262232588 in MIT Press Books. The MIT Press.

——— (2010b): *Solutions manual and supplementary materials for econometric analysis of cross section and panel data*, no. 0262731835 in MIT Press Books. The MIT Press.

Zanello, G. (2012): "Mobile phones and radios: Effects on transactions costs and market participation for households in northern Ghana," *Journal of Agricultural Economics*, 63(3), 694–714.

Zenou, Y. (2012): "Networks in economics," CEPR Discussion Papers 9021, C.E.P.R. Discussion Papers.

Zimmerman, D. J. (2003): "Peer effects in academic outcomes: Evidence from a natural experiment," *The Review of Economics and Statistics*, 85(1), 9–23.